Tracking transient boreal wetland inundation with Sentinel-1 SAR: Peace-Athabasca Delta, Alberta and Yukon Flats, Alaska

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ABSTRACT
Accurate and frequent mapping of transient wetland inundation in the boreal region is critical for monitoring the ecological and societal functions of wetlands. Satellite Synthetic Aperture Radar (SAR) has long been used to map wetlands due to its sensitivity to surface inundation and ability to penetrate clouds, darkness, and certain vegetation canopies. Here, we track boreal wetland inundation by developing a two-step modified decision-tree algorithm implemented in Google Earth Engine using Sentinel-1 C-band SAR and Sentinel-2 Multispectral Instrument (MSI) time-series data as inputs. This approach incorporates temporal as well as spatial characteristics of SAR backscatter and is evaluated for the Peace-Athabasca Delta, Alberta (PAD), and Yukon Flats, Alaska (YF) from May 2017 to October 2019. Within these two boreal study areas, we map spatiotemporal patterns in wetland inundation classes of Open Water (OW), Floating Plants (FP), Emergent Plants (EP), and Flooded Vegetation (FV). Temporal variability, frequency, and maximum extents of transient wetland inundation are quantified. Retrieved inundation estimates are compared with in-situ field mapping obtained during the NASA Arctic-Boreal Vulnerability Experiment (ABoVE), and a multi-temporal Landsat-derived surface water map. Over the 2017–2019 study period, we find that fractional inundation area ranged from 18.0% to 19.0% in the PAD, and from 10.7% to 12.1% in the YF. Transient wetland inundation covered ~595 km² of the PAD, comprising ~9.1% of its landscape, and ~102 km² of the YF, comprising ~3.6%. The implications of these findings for wetland function monitoring, and estimating landscape-scale methane emissions are discussed, together with limitations and uncertainties of our approach. We conclude that time series of Sentinel-1 C-band SAR backscatter, screened with Sentinel-2 MSI optical imagery and validated by field measurements, offer a valuable tool for tracking transient boreal wetland inundation.

1. Introduction
Roughly half of the world’s wetlands are distributed in northern high latitudes (i.e. north of 45°N) (Lehner and Döll 2004; Smith, Sheng, and Macdonald 2007), with a large proportion of them located in the boreal region (Chasmer et al. 2020; Duncan et al. 2020; Watts et al. 2012). Surface water, in the form of inundation or ponding, is a critical factor that directly and...
indirectly influences boreal wetland greenhouse gas emissions and overall carbon balance (Bridgham et al. 2013; Mckenzie et al. 2018; Sebacher, Harriss, and Bartlett 1983). Large seasonal fluctuations in boreal surface water extent occur due to seasonal cycles in snowmelt, summer precipitation, and evapotranspiration demands (Bartsch et al. 2012; Watts et al. 2014). Seasonally flooded wetlands may function as time-varying “hot spots” of methane (CH$_4$) flux relative to adjacent permanently wet and dry areas (Elder et al. 2020; Zou et al. 2022). Such wetlands also serve as important habitats for waterfowl, fish, and other wildlife (Chapman et al. 2015; Webster et al. 2015). They deliver a variety of other functions such as improved water quality, floodwater storage, and ground water recharge, thereby supporting critical ecosystem services to indigenous communities (Kroghman 2006; Rey et al. 2019). The rapid warming of the Arctic affects the distribution of surface and subsurface water due to permafrost degradation and increased evapotranspiration, which eventually alters the hydrology of boreal wetlands (Hinzman et al. 2013). In sum, it is critical to map and monitor transient wetland inundation accurately and frequently for a wide array reasons, such as trace gas emissions, ecological and societal functions, and their sensitivity to climate change.

Remote sensing techniques utilizing visible, infrared, and microwave wavelengths offer effective means for quantifying surface water inundation (Du et al. 2018; Huang et al. 2018; Prigent et al. 2016) and wetland extent (Hondula et al. 2021; Zhang et al. 2021) at varying scales. Due to its long time series and moderate spatial resolution (30 m), Landsat visible/near-infrared imagery is often used for this purpose, including in northern high latitudes (e.g. Amani et al. 2019; Carroll et al. 2016; Wang et al. 2020). Synthetic aperture radar (SAR) is also well suited to wetland studies due to its unique ability to penetrate clouds and darkness, and to detect inundation beneath vegetation canopies (Hess and Melack 2003). L-band SAR is often preferred because its longer wavelength (~24 cm) can penetrate denser vegetation canopies, as well as the strong double-bouncing interactions that occur between inundated forest floors and tree trunks. Several studies have successfully used JERS-1 and ALOS L-band SAR to map boreal wetlands and inundation dynamics (Bourgeau-Chavez et al. 2017; Clewley et al. 2015; Whitcomb et al. 2009). However, in areas with sparse, non-woody vegetation canopies, data from shorter wavelength C-band SAR sensors can also discriminate inundated vegetation (Grandi, Malingreau, and Leysen 1999; Kasischke et al. 2009; Lang, Townsend, and Kasischke 2008; Lang and Kasischke 2008; Manavalan 2018; Townsend 2001; Voormansik et al. 2014). Different C-band SAR sensors, such as ERS-1 and RADARSAT, have been successfully used in many wetland studies (e.g. Bourgeau-Chavez et al. 2005; Brisco et al. 2013, 2019; Clark, Creed, and Sass 2009; Delmeire 1997; Kasischke and Bourgeau-Chavez 1997; Long, Fatoyinbo, and Policelli 2014; Montgomery et al. 2018; Parmuchi, Karschenbaum, and Kandus 2002; Sass and Creed 2008; Toyra, Pietroniro, and Martz 2001).

The use of C-band SAR for wetland mapping has been further advanced by the European Space Agency (ESA) Sentinel-1 mission, a part of the European Union’s Copernicus Programme (Hardy et al. 2019). Sentinel-1 consists of a two-satellite constellation (Sentinel-1A/1B), launched on 3 April 2014 and 25 April 2016, respectively. The constellation can acquire backscatter imagery with different polarization combinations at high spatial resolution (10 m) and high temporal resolution (Martinis, Plank, and Ćwik 2018), with a repeat cycle of just six days. The value of Sentinel-1 SAR for mapping wetland vegetation (e.g. Hardy et al. 2019; Plank et al. 2017; Slagter et al. 2020; Tsyganskaya, Martinis, and Marzahn 2019; Tsyganskaya et al. 2018a), water depth (e.g. Zhang, Wdowinski, and Gann 2022a; Zhang et al. 2022b), and hydroperiod (e.g. DeLancey et al. 2018; Huth et al. 2020; Kasischke et al. 2003; Liang and Liu 2020) are now well established. At least one previous study (Mahdianpari et al. 2020) has confirmed the utility of Sentinel-1 for boreal wetlands. Together with Sentinel-1 SAR backscatter, Mahdianpari et al. (2020), Slagter et al. (2020), and Zou et al. (2021) also used optical Sentinel-2 Multispectral Instrument (MSI) data to obtain additional information on vegetation spectral reflectance.

This study aims to track transient boreal wetland inundation using Sentinel-1 C-band SAR data, with assistance from Sentinel-2 MSI data. The paper is organized as follows. In Section 2, we provide further background from previous studies, identify knowledge gaps and present the specific objectives of this study. Materials and methodology are presented in
Section 3. Inundation mapping results are presented in Section 4. The significance of the results, as well as influence of Sentinel-1 orbit selection, are discussed in Section 5. Some final conclusions, limitations of the study, and possible directions for future research are presented in Section 6.

2. Background

2.1 Previous studies of boreal wetland mapping

The National Aeronautics and Space Administration (NASA) Arctic-Boreal Vulnerability Experiment (ABoVE) is studying environmental changes and social-ecological systems of Alaska and Western Canada (Figure 1, https://above.nasa.gov/). Surface water hydrology is a key research theme for the ABoVE program, because Arctic-Boreal Region warming is impacting climatological water balance and enhancing permafrost thaw, altering the storage of water both above and below ground (Smith et al. 2005; Smith, Sheng, and Macdonald 2007; Walvoord and Kurylyk 2016; Kåresdotter et al. 2021). Arctic-Boreal wetlands contain abundant soil carbon due to low rates of decomposition under anoxic conditions (Moore, Roulet, and Waddington 1998). They often sequester long-term stocks of soil carbon (e.g. MacDonald et al. 2006; Smith et al. 2004; Tarnocai et al. 2009), which may mobilize in a warming climate due to changes in soil temperature, moisture, and disturbance regimes (McGuire et al. 2012; Plaza et al. 2019; Schuur et al. 2015; Vaughn and Torn 2019). Arctic-Boreal wetlands are thus of particular importance for biogeochemical cycles and GHG emissions. Moreover, the hydrological impacts of climate change have varying impacts on ecology and societies, which are major concerns of ABoVE.

Together with airborne data acquisitions (Miller et al. 2019), satellite remote sensing is an important part of the ABoVE research agenda and offers strong capability for studying environmental changes across the Arctic-Boreal Region (Duncan et al. 2020).

A number of geospatial data products for open water, wetland inundation, and land cover have been produced to map Arctic-Boreal water and/or wetland classes (see Table 1), some specially for ABoVE (e.g. Carroll et al. 2016; Bourgeau-Chavez et al. 2019; Wang et al. 2020) and others as continental or global products covering part or all of the Arctic-Boreal Region.

Among these products, Landsat visible/NIR imagery, which offers 30 m spatial resolution and long historical archives, is frequently used. These products generally emphasize open water extent and temporal changes. Another frequently used data source is L-band SAR from the ALOS or JERS satellite missions.

Figure 1. The Peace-Athabasca Delta (PAD) and Yukon Flats (YF) study areas (black boxes) are located within the core region of the NASA ABoVE study domain. Insets show sample Sentinel-1 C-band SAR backscatter images of the PAD (VH on 20 August 2018) and YF (VH on 20 July 2017).
Table 1. Some widely used open water and wetland inundation products from radar and optical satellite remote sensing sources.

| Name                                      | Spatial coverage      | Spatial resolution | Time span        | Temporal resolution | Data sources          | Mapping method       | Reference            |
|-------------------------------------------|-----------------------|--------------------|-------------------|---------------------|-----------------------|----------------------|----------------------|
| ABoVE Surface Water Maps                  | ABoVE study regions   | 30 m               | 1991, 2001, 2011  | annual              | Landsat               | Decision tree         | (Carroll et al. 2016) |
| ABoVE Ecosystem Map                       | Great Slave Lake and its surrounding | 12.5 m | 1997–2011      | mosaic              | Landsat, ALOS L-band SAR | Random forest         | (Bourgeau-Chavez et al. 2019) |
| ABoVE Annual Dominant Land Cover product  | ABoVE Core Domain     | 30 m               | 1984–2014        | annual              | Landsat               | Random forest         | (Wang et al. 2020)    |
| Canadian Wetland Inventory Map-1          | Canada                | 30 m               | 2016–2018        | mosaic              | Landsat-8             | Random forest         | (Amani et al. 2019)   |
| Landsat Dynamic Surface Water Extent      | U.S.                  | 30 m               | 1982–present     | ~16 days            | Landsat               | Multiple water indices| (Jones 2019)          |
| Joint Research Center (JRC) Global Surface Water product | Global               | 30 m               | 1997–present     | monthly             | Landsat               | Expert system         | (Pekel et al. 2016)   |
| Alaska Wetlands Map-1                     | Alaska                | 50 m               | 1998–2007        | mosaic              | JERS-1 L-band SAR     | Random forest         | (Whitcomb et al. 2009) |
| Alaska Wetlands Map-2                     | Alaska                | 50 m               | 2007             | mosaic              | ALOS L-band SAR       | Random forest         | (Clewley et al. 2015)  |
| Circumpolar Wetness Classification Map    | Arctic tundra regions | 1 km               | 2005–2011        | Summer and winter   | Envisat C-band SAR    | Seasonal backscatter difference | (Widhalm, Bartsch, and Heim 2015) |
| Canadian Wetland Inventory Map-2          | Canada                | 10 m               | 2016–2018        | mosaic              | Sentinel-1, Sentinel-2 | Random forest         | (Mahdianpari et al. 2020) |
| Global inundation dynamics product        | Global                | 0.25 arc degree    | 1993–2000        | monthly             | AVHRR, ERS, SSM/I     | Unsupervised clustering| (Prigent et al. 2007) |

Most L-band SAR products, for example, Alaska Wetlands Maps (Whitcomb et al. 2009; Clewley et al. 2015), have high spatial resolution (~12.5–50 m). C-band SAR data from Envisat and Sentinel-1, have also been used for mapping boreal wetlands (e.g. Widhalm, Bartsch, and Heim 2015; Mahdianpari et al. 2020). However, like the aforementioned L-band products, these are composite mosaic products, with no explicit temporal information on inundation dynamics.

2.2 Previous C-band SAR studies of surface water and wetlands

Detecting of surface water with C-band SAR data is generally straightforward for smooth water surfaces, which return low backscatter. However, backscatter increases with wind-, rain-, or turbulence-induced surface roughness, which may cause false detections of water as land (O’Grady, Leblanc, and Bass 2014). Overall, cross-polarized channels are less affected than co-polarized channels (Henry et al. 2006; Schumann et al. 2007; Bangira et al. 2021). The presence of floating macrophyte plants also increases backscatter (Manavalan 2018). Alsdorf et al. (2000) found increased C-band backscatter values due to “double bounce” radar returns from floating aquatic macrophytes and vertical shrubs, as did Horritt et al. (2003) over marshlands. Overall, flooded woody vegetation increases in backscatter due to double-bounce scattering, whereas flooded short, sparse herbaceous vegetation decreases backscatter due to specular reflection of the signal (Pope et al. 1997). Kasischke and Bourgeau-Chavez (1997) found a 4 to 6 dB backscatter decrease in ERS-1 C-band SAR imagery after flooding in a marsh. Martinis and Rieke (2015) summarized backscatter variations between flooded and dry conditions and found that the backscatter enhancement from double bounce varied heterogeneously for C-band SAR, ranging from less than 1 dB to more than 6 dB, depending on environmental and system parameters. They thus concluded that empirically derived threshold values separating flooded from non-flooded area were not transferable and should be defined individually.

One thing that further complicates the situation is that soil moisture and water level were found to be able to change SAR backscatter as well (Kasischke et al. 2003; Lang and Kasischke 2008). This was recently confirmed by Zhang et al. (2022b), who found a linear relationship between Sentinel-1 C-band SAR backscatter and water level, indicating that as the water level increase, the backscatter increases for sparse woody vegetation, but decreases for sparse herbaceous. While most studies considered aquatic vegetation and flooded vegetation as an integral when
detecting wetland inundation using SAR (e.g. Horritt et al. 2003; Tsyganskaya, Martinis, and Marzahn 2019; Sipelgas, Aavaste, and Ulboupin 2021), it was generally agreed that the backscatter from aquatic vegetation stands usually has low values in all wavelengths and polarizations, caused mainly by forward scattering from the water surface and the attenuation of the signal from the canopy (Silva et al. 2008). On the contrary, the backscatter from flooded vegetation generally has high values due to more common double-bounce effect (Alsdorf et al. 2000).

In Flooded Vegetation (FV), co-polarized backscatter (VV or HH) is more sensitive to the double-bounce phenomenon, while cross-polarized (VH) backscatter is more sensitive to volume scattering due to greater depolarization (Marti-Cardona, Dolz-Ripollés, and Lopez-Martinez 2013; Townsend 2002). VV polarization shows a strong increase at the flood date while VH polarization shows low or almost no increase (Tsyganskaya, Martinis, and Marzahn 2019). For these reasons, a combination of co- and cross-polarized data is usually recommended for detecting FV. For example, Brisco et al. (2011) noted that ratios between co-polarized backscatter and cross-polarized backscatter at linear scale were appropriate for distinguishing FV from uplands, consistent with Mougín et al. (1999) and Bangira et al. (2021). Furthermore, Zhao et al. (2014) found that multi-temporal classifications could better capture the spatial distribution of FV than one-time classifications, which often showed large variability due to the effect of phenology and flooding. This suggests that temporally averaged cross-polarized backscatter may be a good proxy for different vegetation types. Similarly, time series approaches are recommended for FV studies, to account for seasonal or annual fluctuations in inundation (e.g. Bangira et al. 2021; Schlaffer et al. 2016; Tsyganskaya et al. 2018a).

During inundation, FV backscatter varies up to one order of magnitude (Grimaldi et al. 2020), making it difficult to discern from other causes of backscatter variation (Plank et al. 2017). Moreover, there is considerable overlap between bright targets (e.g. swamps and uplands) due to their combinations of double bounce and volume scattering, which effectively reduces separability among inland and wetland classes (Brisco et al. 2019). Although some dual polarization-based vegetation indices (e.g. Chang, Shoshany, and Oh 2018; Chang, Oh, and Shoshany 2022) may be helpful for separating inland and wetland vegetation from the perspective of vegetation biomass difference, polarimetric decomposition on fully polarimetric is more often employed to mitigate this problem (Brisco et al. 2011). However, fully polarimetric data are generally unavailable over large areas and long time periods. An alternative solution is to employ other sources of information such as visible/NIR images, digital elevation models (DEM), and/or land cover classification maps to help mask out upland areas and aid detection of flooded vegetation classes (Grimaldi et al. 2020). Supervised and unsupervised methods have also been applied to identify FV from SAR imagery, but massive training samples and/or extensive ancillary information are required to achieve reliable results (Tsyganskaya et al. 2018b).

2.3 Objectives of this study

This study aims to present a practical and effective framework for monitoring boreal wetland inundation dynamics at high spatial and temporal resolutions using time series of dual-polarized (V/VH) Sentinel-1 SAR imagery and multi-spectral Sentinel-2 MSI optical imagery. Our approach capitalizes on differing backscatter characteristics of various inundation components of a typical boreal wetland, as well as their spatial adjacency to each other (i.e. as ephemeral inundation commonly surrounds open water bodies), so as to facilitate the classification and reduce the need for ancillary data. In this study, wetland inundation components refer to those land cover types that are permanently or occasionally inundated, that is, Open Water (OW), Floating Plants (FP), Emergent Plants (EP), and Flooded Vegetation (FV). A time series analysis of SAR backscatter intensity is used to generate a maximum likely inundation map, to constrain the mapping and mitigate the large range in backscatter due to heterogeneous vegetation types and phenology. To help discriminate different land classes having similar radar backscatter returns, we incorporate Sentinel-2 MSI derived Normalized Difference Vegetation Index (NDVI) to identify vegetation coverage. This particularly helps flag Floating Plants which are difficult to distinguish from rough open water surface using SAR (Manavalan 2018). We test this
methodology for two selected boreal study areas (Peace-Athabasca Delta, Alberta, and Yukon Flats, Alaska), for which field validation data were previously collected for NASA ABoVE (Kyzivat et al. 2021). Spatiotemporal patterns in OW, FP, EP, and FV for these two study areas are derived and analyzed, as described next.

3. Materials and Methods

3.1 Peace-Athabasca Delta and Yukon Flats study areas

Two boreal areas with extensive wetlands were selected for this study, the Peace-Athabasca Delta (PAD) in northern Alberta, Canada, and the Yukon Flats (YF) in north-central Alaska, USA (black rectangles, Figure 1). These two sites, with areas of ~3400 km² and ~1139 km² respectively, are important boreal wetland habitats for which improved mapping of transient wetland inundation patterns would aid studies of methane flux (Balsal and Wylie 2010), wildlife habitat (Peters et al. 2006), and ecological services for indigenous communities (Krogman 2006; Rey et al. 2019). Boreal wetlands are diverse in form and function and can be classified into five major types: bogs, fens, swamps, marshes, and shallow open water wetlands (Gingras et al. 2016). Figure S1 in the Supplementary Information (SI) shows a collection of field photos for the four typical wetland types. Photos of bogs are not showing as bogs usually have no open water bodies and are thus not our studying focus.

The PAD is the world’s largest inland boreal delta, a Ramsar Wetland of International Importance, and part of a UNESCO World Heritage Site with “in Danger” status pending (Ward and Gorelick 2018). It is hydrologically active with abundant lakes and wetlands that recharge seasonally in response to annual discharge cycles in the Athabasca River (Pavelsky and Smith 2008, 2009). Climate change and river regulation are causing extensive wetland drying in this area (Beltaos 2014; Beltaos and Peters 2020; Wolfe et al. 2020), with cascading consequences for its flora and fauna communities. Due to river regulation, the Peace River, for example, has experienced a reduction in median daily flow from 3600 m³/s to 2350 m³/s since 1972, and there is an ongoing debate about the existence of a causal relationship between dam regulation and a subsequent decrease in ice-jam flooding and associated water wetland replenishment downstream of the dam (Timoney 2021; Beltaos 2014; Wolfe et al. 2020). Common plant communities in the PAD include sedges, grasses, meadows, willow thickets and forests. Excluding its three largest lakes (Lake Claire, Mamawi Lake, and Richardson Lake), the PAD is comprised of ~31% aquatic communities, ~34% marshes, ~23% savannahs and thickets, and ~8% forests (Timoney 2008).

The YF is a lake-rich lowland found along a ~100 km low-gradient, anabranching section of the Yukon River. It encompasses the Yukon Flats National Wildlife Refuge, and has been identified as an ecologically sensitive region poised for major hydrologic change due to permafrost degradation from climate warming (Pitcher et al. 2019; Walvoord, Voss, and Wellman 2012). Annual high flows in the Yukon River and its tributaries occur during the summer melt season. On the main stem of the Yukon for example, flood peaks can reach up to ~20,000 m³/s (Brabets, Wang, and Meade 2000). Wetlands and lakes are present throughout the YF, interspersed with numerous tributaries and distributary channels. Its landscape is patterned with braided and meandering streams, numerous thaw and oxbow lakes, and meander scars (Brabets, Wang, and Meade 2000). Lakes are abundant, with broad range of sizes (Rey et al. 2019). Yukon Flats is known for its highly productive wetlands surrounded by meadows and numerous bogs, marshes and heterogeneous forest. Vegetation classes consist mainly of Arctic tundra, alpine tundra, taiga (subarctic forest), boreal forest and subalpine-shrub forest, with graminoid herbaceous communities being the predominant vegetation type (Brabets, Wang, and Meade 2000).

3.2 Remote sensing data

Sentinel-1 scans the Earth systematically with a revisit frequency up to 6 days. It acquires high resolution (5 ~ 40 m, depending on mode) C-band SAR data with a stable 18°~46° incidence angle, enabling direct comparison of all images from the same orbit track as they exhibit identical shadowing and layover effects (Cian, Marconcini, and Ceccato 2018). To maximize spatial resolution and enhance flooded vegetation detection, dual-polarized (VV and VH) data in the Sentinel-1 Interferometric Wide swath (IW) Ground Range
Detected (GRD) High Resolution product with 10 m resolution were used.

All Sentinel-1 images have previously been preprocessed (thermal noise removal, radiometric calibration, and terrain correction) with the Sentinel-1 Toolbox and stored on the Google Earth Engine (GEE) platform (Gorelick et al. 2017). Terrain correction of Sentinel-1 data has been performed using the SRTM DEM for latitudes <60° and the ASTER DEM for latitudes >60° before being uploaded to the platform. Because surface water freezes in winter in the study areas, only the ice-free months (May to October) were examined in this study. Sentinel-1 images of the PAD and YF were obtained from May to October in 2017–2019, as per DeLancey et al. (2018). To ensure consistency in incidence angle, we used only repeat-pass Sentinel-1 data collected from the same orbit tracks. Based on these criteria, a total of 41 and 67 Sentinel-1 SAR scenes (13 ~ 29 scenes per year) were selected for the PAD and YF, respectively. Selected Sentinel-1 images were accessed from the GEE environment and smoothed with a 3 x 3 Sigma Lee filter after trialing different sizes of filtering window. Although Lu et al. (2011) found better land cover mapping performance with a 5 x 5 window, we found a 3 x 3 window is more appropriate for this study, particularly for extracting small river channels.

Because C-band SAR cannot differentiate between wind-roughened open water and floating plants (Manavalan 2018), we also employed Sentinel-2 Multispectral Imager (MSI) visible/NIR imagery as ancillary data. Optical images readily discern Floating Plants (and other vegetation) due to their strong near-infrared reflectance of chlorophyll, and thus offer a useful alternative to SAR for distinguishing wind-roughened water surfaces from Floating Plants. Using Sentinel-2 MSI imagery, we calculated an annual maximum Normalized Difference Vegetation Index (NDVI) based on May–October MSI images available in GEE. The usage of annual maximum NDVI instead of NDVI calculated from individual Sentinel-2 images also alleviates image contamination from clouds and reduces computational cost.

### 3.3 Field validation data

In a previous study, some of the authors conducted field mapping surveys in the YF and PAD, yielding an extensive in situ dataset of inundation status and vegetation functional type (Table S1 in the SI) (Kyzivat et al. 2021, 2022). In total, this dataset contains 290 and 419 sites in the YF and PAD, respectively. This dataset was derived from field observations and augmented with existing remote sensing datasets. The primary method of field observation was GPS tracks corresponding to inundation extent and aquatic vegetation boundaries. These GPS tracks were collected with the goal of validating inundation classification based on the L-band UAVSAR instrument, which flies ongoing sorties over the PAD as part of the NASA ABoVE airborne campaign. However, they are general enough to validate any inundation classification at a similar spatial scale from the same period. Lakes and wetlands were chosen advantageously, based on accessibility within the delta, which generally required being within ~500 m from a navigable river channel. As a result, nearly all polygons corresponding to GPS tracks were located adjacent to water bodies. The GPS tracks were used to interpret current land cover and inundation status with the assistance from ~70,000 field photos and UAV color-infrared images from the ground, high-resolution airborne color-infrared camera (CIR) imagery acquired as part of the ABoVE AirSWOT flight campaigns (Kyzivat et al. 2019; Fayne et al. 2020), and other ABoVE land cover datasets (Bourgeau-Chavez et al. 2019; Wang et al. 2020). Due to this augmentation, polygons could be selected throughout the study area to avoid the clustering effect caused by field access requirements. They were drawn making use of existing water-vegetation boundaries and only contain one land cover class, which can be a mixture of vegetation types.

Major wetland vegetation classes in this dataset include wet forest (WF), wet shrub (WS), wet graminoid (WG), and wet herbaceous (WH) plants. A complete listing of all field-validated vegetation classes found within our YF and PAD study areas is shown in Table S1. In general, WF, WS, and WG are Flooded Vegetation, WH mostly corresponds to Aquatic Vegetation, which includes Floating Plants (e.g. pond lily *Nuphar* spp.) and Emergent Plants (e.g. pondweed *Potamogeton* spp.). Moreover, while two categories of surface water were noted in the field, it is inappropriate to use them to characterize water surface roughness at the exact instant of Sentinel-1 SAR overpasses. Therefore, we combined these two categories into a single “Open Water” category. Of all
the field samples, 20% of them were randomly selected for each class as training samples to calibrate the method, and the remaining was used as validation samples to evaluate the inundation mapping results.

### 3.4 Inundation mapping

In this study, we focus on mapping inundation components of only those wetlands having at least one open water surface somewhere within their extent. This limitation means that pond-free bogs or fully vegetated marshes, for example, are not included in this analysis. The reason for this requirement is that open water bodies are commonly surrounded by wetland vegetation, making spatial adjacency to the former a strong predictor of the latter.

A conceptual illustration of this assumption is presented in Figure 2a. Inundated wetland vegetation may be broadly subdivided into two categories, perennially inundated aquatic vegetation, and temporarily flooded vegetation. Perennially inundated aquatic vegetation may be further divided into three classes, Emergent Plants (EP), Floating Plants (FP) and Submerged Plants. Since submerged plants grow under the water surface, they are not observable with SAR, so this class is hereafter ignored. Floating Plants are annuals, and thus their distribution changes seasonally and from year to year. Emergent Plants are typically inundated at least partially with standing water, but may also have no water during very dry conditions or become totally submerged during very wet conditions. In addition to perennially inundated aquatic vegetation, surrounding terrestrial/riparian plants may also be temporarily flooded, here called Temporarily Flooded Vegetation. Temporarily Flooded Vegetation signifies any pixel on the maximum inundation map that was inundated at least once during the observing period (2017–2019). Flooded Vegetation (FV) signifies any vegetation pixel on a single inundation map (i.e. a particular date) was inundated. Both Aquatic Vegetation and Temporarily Flooded Vegetation occupy the temporarily transient/ephemeral inundated zone of wetlands, which tends to surround and/or be adjacent to Open Water (OW) bodies.

We present a two-step inundation mapping methodology (Figure 2b) to map both OW and inundated vegetation (i.e. FP, EP, and FV) from Sentinel-1 SAR time series, with Sentinel-2 MSI derived NDVI imagery as the only ancillary. The first step aims to estimate maximum observed inundation extent over certain time period (here May 2017 – October 2019), which once determined, is then employed to constrain the second step, single scene wetland inundation mapping. Figure 2b presents the conceptual framework for this two-step workflow. Its core premise is that both Aquatic Vegetation and Temporarily Flooded Vegetation are likely to surround or be adjacent to OW. Because OW is easier to detect, this framework simplifies remote sensing of permanently and transiently inundated wetland vegetation.

A modified decision-tree classification method based on the framework in Figure 2 was developed to discern different types of transient and permanent wetlands inundation according to their SAR backscatter characteristics (Figure 3). Step-1 identified the maximum wetland inundation extent using backscatter time series statistics, generated on a pixel-by-pixel basis within the GEE platform using a max/mean/min reducer method on the GEE platform. We assumed maximum recorded VH to

Figure 2. (a) Wetland inundation components, (b) conceptual framework of wetland inundation mapping.
represent the driest observable condition and minimum recorded VH polarization to represent the wettest observable condition over the observation period. VH was used instead of VV due to its lower sensitivity to surface water roughness (Henry et al. 2006; Schumann et al. 2007; Bangira et al. 2021). Permanent WET and Temporary WET pixels were then identified from maxVH and minVH using high and low thresholds, respectively (see Table 2). The Temporary WET category includes Intermittent Open Water and emergent Aquatic Vegetation surrounding this water. Temporarily Flooded Vegetation was identified by thresholding the quantity maxVV – meanVH, to capitalize on double bounce returns from flooded vegetation that induce high VV backscatter (Tsyganskaya et al. 2018b). As the cross-polarized backscatter (VH) is sensitive to volume scattering (Marti-Cardona, Dolz-Ripolles, and Lopez-Martinez 2013; Townsend 2002), the mean value of time series VH backscatter (meanVH) was used because it represents a backscatter baseline for different vegetation types. We used this subtraction operation at dB scale, as Mougin et al. (1999) and Brisco et al. (2011) both recommended that ratios

Figure 3. Modified decision-tree classification for wetland inundation mapping. T1-T7 represent thresholds used for each tree node, as per Table 2. Red boxes summarize the classes in different resultant maps of this method.

### Table 2. Description of decision-tree thresholds presented in Figure 3.

| Threshold | Thresholding target | Thresholding strategy | Principle and assumptions |
|-----------|---------------------|-----------------------|---------------------------|
| T1        | maxVH               | OTSU threshold of Generally Open Water samples | Among all the Generally Open Water samples, a large part should be Permanent WET, which can be identified from the driest scenario (reflected by maxVH). |
| T2        | minVH               | 3-sigma rule (η + 3σ6) of Generally Open Water samples | In the wettest scenario (reflected by minVH), most of the Generally Open Water samples should be Temporary WET, except for some outliers. |
| T3        | maxVV – meanVH      | Fixed value (12)       | Temporarily Flooded Vegetation was identified from enhanced VH backscatter due to double-bounce effect, differentiated by the vegetation types (reflected by meanVH). Threshold was determined empirically to ensure that most of the observed samples could be included. |
| T4        | maxNDVI             | Fixed value (0.30)     | An empirical threshold was determined from visual inspection or literature to distinguish vegetation from non-vegetation from annual maximum NDVI image. |
| T5        | VH                  | 2-sigma or 3-sigma rule (η + kσ6) of Permanent WET samples | Generally Permanent WET samples should be Open Water, except for some outliers. |
| T6        | VH                  | T5 + Δ (3.0 dB)        | Emergent Plants have a slightly higher backscatter than Open Water and Floating Plants, due to their higher volume scatter from the canopy. Δ was determined empirically with the assistance of observed field samples. |
| T7        | VV – meanVH         | Hysteresis thresholding ([T3 – ΔVV, T3]) | Flooded Vegetation was identified from double-bounce effect, differentiated by the vegetation types (reflected by meanVH). Hysteresis thresholding strategy was adopted to preserve the spatial connectivity. |
between co-polarized backscatter and cross-polarized backscatter at linear scale, which equates with subtractions at dB scale, are appropriate for distinguishing FV from uplands. Except for Permanent Wet, Temporary Wet, and Temporarily Flooded Vegetation, all remaining pixels were classified as Permanent Dry in the Step-1 maximum inundation map product. Temporarily Flooded Vegetation patches distal from Permanent Wet or Temporary Wet pixels, reflected as Euclidean distance greater than a predetermined limit, were considered false detections, and reassigned as Permanent Dry. This distance limit was set to 30 m, as we determined a three-pixel distance being sufficiently far to be deemed “disconnected” based on inspection of high-resolution CIR imagery (Kyzivat et al. 2019). A filtering procedure was conducted to remove small patches and holes smaller than a predetermined limit of nine Sentinel-1 SAR pixels, as we found no wetlands smaller than this size in the high-resolution CIR imagery. The nine-pixel minimum was applied to wetlands as well as open water bodies.

Next, a Step-2 inundation map was generated for each Sentinel-1 SAR image based on its VV and VH backscatter, using potential wet and flooded pixels of the Step-1 maximum inundation map as a constraint. Annual maximum NDVI images derived from Sentinel-2 MSI images were also employed to separate vegetated and non-vegetated areas. We assume that Emergent Plants are likely to be short, sparse herbaceous vegetation that usually have low backscatter and show decrease in backscatter when flooded, while Flooded Vegetation is likely to be woody vegetation that have increased backscatter due to double-bounce scattering. Our modified decision-tree classification approach used seven thresholds (T1-T7, see Figure 3 and Table 2) to define decisions separating the different inundation components. The end result of this process yielded five classes for each Step-2 inundation map, namely: Open Water (OW), Floating Plants (FP), Emergent Plants (EP), Flooded Vegetation (FV), and Dry land (Dry). This map may be further generalized to four classes by aggregating FP and EP as Aquatic Vegetation, or three classes (OW, IV, and DRY) by further aggregating Aquatic Vegetation and Flooded Vegetation as Inundated Vegetation, as needed for different applications.

3.5 Determination of decision-tree thresholds

Seven thresholds used to generate the described scene-level Step-2 wetland inundation maps (Table 2) were determined as follows:

Otsu thresholding (Otsu 1979), which seeks an optimal threshold that maximizes inter-class variation, was performed on meanVH to determine the optimal threshold for identifying generally Open Water pixels. Time series mean value of VH polarization (meanVH) was used considering that cross-polarized channels are less affected than co-polarized channels for detecting open water (Henry et al. 2006; Schumann et al. 2007; Bangira et al. 2021). Our investigation of our own data also found that meanVH differentiates open water better than meanVV (Figure S2 in the SI). Generally Open Water pixels represent areas of persistent open water in Sentinel-1 time series, as their mean backscatter is significantly lower than other areas. Note that the Generally Open Water class does not correspond to a probability (i.e. likelihood of a pixel being open water), but rather signifies the general presence of an unvegetated open water surface for most multitemporal observations. Generally Open Water pixels may be considered as “high-confidence” open water areas that nonetheless may become non-water in dry seasons.

Another Otsu thresholding (T1) of maxVH values for all Generally Open Water pixels, was used to classify Generally Open Water pixels having relatively low maxVH values (≤ T1) as Permanent WET, because they have consistently low VH values across the entire time series. A threshold value (T2) was applied on minVH for identifying Temporary WET pixels. T2 was determined according to the value distribution of minVH. As calculating standard deviation of log scale (dB) SAR backscatter is inappropriate (Kasischke and Fowler 1989), we calculated 68% of minVH values that are close to the median value ($\eta$), and took the upper boundary of the 68% backscatter values as the surrogate of standard deviation according to the Empirical Rule in statistics, which is marked as $\delta$. A value of $\eta + k\delta$ was determined for T2, with the integer k being set to 3 through trial and error. Lastly, the threshold for Temporarily Flooded Vegetation (T3) was set to 12 dB through trial and error.

For Step-2 inundation mapping, an NDVI threshold (T4) was used to separate vegetated from non-vegetated areas in Sentinel-2 MSI visible/NIR imagery.
Determination of this threshold was straightforward, with an empirical value of 0.30 determined through trial and error with visual inspection of high-resolution Google Earth images. Use of NDVI is particularly helpful for identifying floating vegetation, because backscatter returns from floating vegetation are similar to open water surfaces but yield significantly higher NDVI values. Similarly, because Permanent Wet pixels provide useful information regarding the backscatter distribution of water bodies, $\eta$ and $\delta$ of VH values were calculated for all Permanent Wet pixels. T5 was set to $\eta + kx\delta$, with $k$ determined according to the value range of $\delta$. Higher $\delta$ signifies more fluctuations in backscatter due to higher surface roughness, requiring a smaller $k$ to be applied. Here, $k$ was set to 2 when $\delta > 3$ dB, and set to 3 otherwise.

EP pixels usually have slightly higher backscatter than open water bodies due to volumetric backscatter of above-water vegetation structure. This phenomenon is well established in the published literature (e.g. Alsdorf et al. 2000; Manavalan 2018; Hardy et al. 2019). Therefore, T6 was set to T5 + $\Delta t$, with optimal $\Delta t$ determined as 3 dB through trial-and-error testing with the assistant of the field samples (Kyzivot et al. 2019). A hysteresis thresholding strategy (Canny 1986) was applied to (VV – meanVH) to identify FV pixels. As was mentioned before, meanVH is used because it represents a time-averaged backscatter baseline for different vegetation types. We use the subtraction operation (VV – meanVH), because Mougin et al. (1999) and Brisco et al. (2011) both recommend that ratios between co-polarized backscatter and cross-polarized backscatter at linear scale are appropriate for distinguishing FV from uplands, and a subtraction operation for a dB (logarithmic) scale is equivalent to a ratio operation at linear scale. Hysteresis thresholding uses two threshold levels: $t_{L}$ (low) and $t_{H}$ (high). Values below $t_{L}$ were discarded, values above $t_{H}$ were classified as FV, and values between $t_{L}$ and $t_{H}$ were classified as FV, only if they are adjacent to other FV pixels. In this study, $t_{L}$ and $t_{H}$ were set to be (T3 – $\delta$VV) and T3, respectively, with $\delta$VV representing the 68% of VV backscatter time series close to their median. This approach has been widely used for mapping flooded vegetation (Cazals et al. 2016) and river centerlines (Işıkdoğan, Bovik, and Passalacqua 2017), and preserves spatial connectivity of flooded vegetation while reducing spurious positives. Here, as the hysteresis thresholding is not a hard thresholding but relies more on the spatial adjacency to high-certain inundated pixels, the disturbance caused by VV variation due to water level change and phenology is further limited.

Only repeat-pass Sentinel-1 data collected from the same descending orbit tracks were used in the above computations, to minimize the effects of variable incidence angle. In principle, inclusion of ascending orbit tracks data would double our temporal resolution. However, owing to insufficient ascending orbit data coverage over the PAD and our desire to maintain consistent incidence angles, we restricted our analysis to descending tracks only. To assess sensitivity of the described inundation mapping methodology to the choice of Sentinel-1 orbit track, a sensitivity analysis was performed for the Yukon Flats, replicating the above methods for ascending vs. descending time series of Sentinel-1 SAR imagery (Section 5.1).

### 3.6 Validation and cross comparison

We used the field-mapped validation data of Kyzivot et al. (2021) described previously in section 3.3, as the reference to assess the accuracy of our inundation mapping results. As this dataset was not developed specifically for this study, it contains more and slightly different classes than ours (Table S1), so we generalized both datasets into just three simple classes (Dry, Open Water, and Inundated Vegetation) to facilitate their cross-comparison. Moreover, the field observations are asynchronous with most Sentinel-1 observations, so we used only those field observations collected within 3 days of a Sentinel-1 image (~25.5% of all samples) for validation purposes. To do this, the selected vector-based field maps were rasterized to 10 m resolution and confusion matrices, overall accuracy, commission errors, and omission errors were computed and used to assess accuracy. This assessment was carried out for Step-2 inundation maps only, as Step-1 maps contain no explicit land class information and characterize time-averaged inundation status.

The JRC global surface water product (Pekel et al. 2016), which was derived from all available Landsat data using an expert classification system, has spatial (30 m) and temporal (monthly) resolutions similar to our Sentinel-1 product, and also overlaps with our time series. We conducted a cross comparison between the two approaches, by aggregating our Sentinel-1
mapping results to a monthly time step, and resampling the JRC product to 10 m resolution. Their differences in inundation frequency during 2017–2019 were calculated and pixel number of monthly inundation frequency differences were counted.

4. Results

4.1 Accuracy assessment from field surveys

Our Step-1 maximum inundation maps (Figure S3 & S4 in the SI) reveal a generally reasonable maximum extent of wetland inundation components, which could serve as a constraint for the subsequent Step-2 inundation mapping. The Step-2 inundation maps demonstrate reasonably successful classification of Open Water, Aquatic Vegetation, Flooded Vegetation, and Dry land, as compared with field mappings at both study sites (Figures 4 and 5). However, some field mapped areas, in particular wet shrubs (WS) and wet forest (WF), are incorrectly mapped (e.g. Figure 4b). Through visual inspection, we find that Sentinel-1 backscatter returns within these areas resembles dry areas (DS and DF), likely signifying lack of canopy penetration by C-band SAR due to its relatively short wavelength (Tsyganskaya et al. 2018b). Furthermore, Sedimentary Bars (SB) along the Yukon River are often identified as Open Water (Figure S5d), perhaps due to high sand/gravel moisture (Smith et al. 1996; Williams and Greeley 2004). Considering that the SB class is usually with water riffle and thus largely inseparable from Open Water, SB samples in the field validation dataset were treated as Open Water.

Being collected within 0–3 days of each Sentinel-1 image, the field validation samples of Kyzivat et al. (2021) enable quantitative accuracy assessment of our Sentinel-1 mapping results. The confusion matrices for both study areas are shown in Figure S5 in the SI. It is observed that most of the inundated wetlands mapped in the field are detected correctly in Sentinel-1 imagery. The overall accuracy for the PAD is 74.9%, and that for the Yukon Flats is 86.0%. Most of the errors occur as omission errors, misclassifying Inundated Vegetation as Dry. This is largely because C-band SAR cannot penetrate high and dense canopies (Tsyganskaya et al. 2018b), such as Wet Shrub and Wet Forest. We further calculated confusion matrices that excluded Wet Shrub and Wet Forest (Figure S6 in the SI). Then, the overall classification accuracy for the PAD and Yukon Flats increases to 93.2% and 92.0%, respectively.

While these results suggest high overall classification accuracy, it is important to note that dry

Figure 4. (a) Inundation and wetland extent of the Peace-Athabasca Delta (PAD) on 15 August 2019, as estimated from Sentinel-1. Enlarged areas (b) and (c) provide comparison with field validation data of Kyzivat et al. (2021) (shown as polygons).
land has >98% accuracy and makes up over 69% of the study domain. However, for the Open Water class, omission errors are more common than commission errors, suggesting that our method is conservative. For PAD Inundated Vegetation, omission error (33.3%) is higher than commission error (20.2%), whereas commission error (72.4%) exceeds omission error (30.8%) for the Yukon Flats. This high commission error is largely caused by apparent misclassification of Open Water as Inundated Vegetation. While it is possible that these areas are in fact correctly identified by Sentinel-1 (they have high NDVI values, defining them as Inundated Vegetation according to our methodology), they were identified as Open Water in the field surveys (Kyzivat et al. 2021), suggesting the high NDVI may in fact be from subaqueous plants beneath the open water surface. However, as the field surveys did not notate subaqueous plants in the validation dataset, unfortunately we can neither confirm nor refute this inference at this time. It is noted that by raising the NDVI threshold (T3), it is possible to reduce some of these errors, but we are reluctant to do that because it would probably omit vegetation cover in other locations. Also, we are not particularly disturbed by this particular commission error, as both Open Water and Inundated Vegetation are inundated classes that are later combined for our scientific goal of identifying total wetland inundation extent. If this particular type of misclassification is removed from the total error, Yukon Flats commission and omission errors resemble those of the PAD, with values of 30.8% and 23.9%, respectively.

4.2 Spatiotemporal inundation dynamics

4.2.1 Spatiotemporal inundation dynamics of the Peace-Athabasca Delta (PAD)

In total, 41 wetland inundation maps were created for the PAD (2017–2019). Aggregating these maps into four classes, Dry, Open Water, Aquatic Vegetation, and Flooded Vegetation allows visualization of overall temporal variability of the inundation classes (Figure 6). Of these, FV varies from ~20 km² to ~100 km², comprising 1.3–6.3% of non-dry land and 0.3–1.5% of the overall landscape. While the total wetted area (i.e. sum of all three classes), appears relatively stable across all three years, the open water fraction in 2018 is larger, and aquatic vegetation fraction lower, than the other two years. We attribute this to Aquatic Vegetation (in particular Floating Plants) being less prevalent in 2018. The intra-annual area variation of Open Water is small,
mainly due to proportionally large static lake areas. We overlaid the inundation maps by year and generated three annual maximum inundation maps (Figure 6). It is observed that while the Open Water is relatively stable throughout the year, Inundated Vegetation, which is the leftover part of subtracting annual maximum inundation with annual maximum OW, seems quite variable, suggesting dramatic seasonal spatial variations with each year.

Stacking all 41 inundation maps over the period 2017–2019 enables creation of an inundation frequency map (Figure 7). In this map, higher values signify more frequently inundated areas (with a maximum value of 41 representing permanently

![Figure 6](image_url) **Figure 6.** Time series of Peace-Athabasca Delta Open Water (OW, in blue), Aquatic Vegetation (AV, in pink), and Flooded Vegetation (FV, in green) areas from May to October (2017–2019).

![Figure 7](image_url) **Figure 7.** (a) 2017–2019 transient wetland inundation frequency of the Peace-Athabasca Delta (PAD), including two enlarged areas (b) and (c). Pixel values represent the number of time that each pixel was detected as wet (Open Water, Aquatic Vegetation, or Flooded Vegetation) in all available Sentinel-1 SAR observations (41 in total).
inundated pixels across all satellite observations). Transiently inundated wetlands are defined as those pixels having inundation frequency values less than 41 but greater than 0. Based on this definition, transient wetland inundation covered ~595 km$^2$ of the PAD over the period May 2017–October 2019, comprising ~37.3% of the wetted landscape and ~9.1% of the overall study area. It is observed from Figure 7 that inundation frequency generally decreases from open water bodies to their peripheries. This mainly because that the wetlands are accumulation zones of surface water. This spatial pattern affirms the central assumption of our conceptual framework, which assumes that wetland inundation tends to surround and/or radiate from open water bodies. While even larger changes in PAD inundation are caused by flow reversals from the Peace River during ice-jam floods (Peters et al. 2006). Figure 7c suggests that small inundated area differences over the study period were driven by local Aquatic Vegetation dynamics rather than riverine flooding.

4.2.2 Spatiotemporal inundation dynamics of the Yukon Flats (YF)
In total, 34 wetland inundation maps were created for the YF (May to October, 2017–2019). The temporal variability of inundated areas (Figure 8), including Open Water, Aquatic Vegetation and Flooded Vegetation, shows a similar pattern to that of the PAD (Figure 6). Wet areas in this site were also stable, but Flooded Vegetation areas were variable. There is a negative annual water budget (Chen et al. 2014; Ford and Bedford 1987) in this region, as in the PAD, which explains the summer recessions in inundated area (Cooley et al. 2019). The percentage of YF inundation area (including Open Water) in this site ranged from 10.7% to 12.1%, while the PAD ranged from 18.0% to 19.0%. Inundation fraction in the YF was statistically more variable than that in the PAD. The higher variation in percentage of inundated area may be due to the diversity of underlying geology, permafrost conditions and relative topology in Yukon Flats lakes (Cooley et al. 2017; Turner, Wolfe, and Edwards 2010; Pitcher et al. 2019). However, annual maximum YF inundation areas suggest that spatial variations within each year are much smaller than that of the PAD (Figure 8). Similarly, YF inundation frequency (Figure 9) exhibits less spatial variation. Applying the same method as for the PAD, we found that maximum inundation extent was 12.9% of the total area of the Yukon Flats study area, while the percentage in the PAD was 24.5%. The area of transient wetland inundation in the Yukon Flats site was ~102 km$^2$, totaling ~27.9% of the wetted landscape and ~3.6% of the total study area. In sum, the Yukon Flats area exhibits much lower spatiotemporal inundation variability than the Peace-Athabasca Delta.

4.3 Comparison with a Landsat global surface water product
Fifteen monthly inundation maps for the PAD (Figure 10), and eight for the YF (Figure 11) are coincident with the JRC water product (Pekel et al. 2016). Positive differences indicate higher inundation occurrence/frequency in the Sentinel-1 maps, whereas negative differences indicate lower inundation occurrence/frequency. In the frequency histograms (Figure 10d, 11d), the frequency of values agreements (difference = 0) in both products are not shown, due to their much larger pixel counts. For both sites, positive

Figure 8. Time series of Yukon Flats Open Water (OW, in blue), Aquatic Vegetation (AV, in pink), and Flooded Vegetation (FV, in green) areas from May to October (2017–2019).
differences are more extensive, signifying that inundation occurrence is generally more prevalent in our Sentinel-1 product than the JRC product. Three major reasons for this are: 1) some inundated vegetation, including Floating Plants, is missed in the JRC product but captured in Sentinel-1 imagery; 2) some water bodies in the JRC product may be missed due to cloud obstruction in Landsat imagery; 3) small georeferencing errors between the two products introduce inconsistencies, particularly along river shorelines (e.g. Figure 10c and Figure 11b). However, lower inundation occurrence was also observed in our product, mainly along the borders of open water bodies (e.g. Figure 11c), likely due to commission errors in JRC products due to mixed pixels from Landsat’s coarse spatial resolution.

5. Discussion

5.1 Descending vs. ascending orbits

The sensitivity of our approach to different orbit tracks (i.e. descending vs. ascending) was tested at the Yukon Flats site. Using a time series of ascending-orbit images, inundation maps were generated using the identical procedure as used for descending orbit images. We observed consistent retrieval of inundation extents with both ascending and descending orbits (Figure 12), with inundation area varying mainly with T5 threshold changes. T5 threshold values were generally higher for descending orbits than for ascending orbits, most likely due to incidence angle differences between the two tracks. To avoid manual adjustment and human intervention, this conclusion was made from a statistical strategy for thresholding specifically a 2-sigma or 3-sigma rule applied to Permanent Wet samples.

Combining ascending and descending orbits introduces different incidence angles and hence backscatter for the same ground location, thus introducing additional uncertainty to the results. We conclude that both ascending and descending tracks yield useful inundation retrievals but should be processed as separate time series rather than combined in a single time-series. Over broader study areas, additional processing of all overlapping orbits is likely necessary, as overlapping likely affects the thresholding procedure presented here. Future research should seek to mitigate this problem, to allow tracking of spatiotemporal inundation dynamics of the whole ABoVE region (Figure 1) or continental/global scales.
5.2 Significance of the wetland inundation maps

Boreal wetlands are diverse in form and function, and offer a variety of ecosystem services that are important at local, regional, and global scales. The selected two study areas (PAD and YF) in particular, are two major wetland complexes that serve as important wildlife habitat and also support the livelihood of indigenous peoples. This study, providing inundation dynamics at uniquely high spatial and temporal resolutions, facilitates monitoring these important regions in the context of climate-caused hydrologic change. Wetland methane emissions, for example, are the largest single natural source in the global CH$_4$ budget (Kirschke et al. 2013), and transient wetlands are hotspots of CH$_4$ fluxes (Tangen and Bansal 2019). Moreover, different inundation components have differing rates of CH$_4$ flux, with Emergent Plants, for example, emitting more CH$_4$ than floating or submerged plants (Laanbroek 2009). It is therefore important to identify transiently inundated wetlands and vegetation classes, especially on boreal landscapes which experience strongly seasonal cycles in landscape inundation. Our approach, which discerns different wetland inundation components with both high spatial and high temporal (~bi-weekly) resolutions, allows this and could therefore provide temporally varying input to CH$_4$ models (e.g. Petrescu et al. 2010), unlike static wetland maps or visible/NIR-based open water products (Table 1).

The Yukon Flats and Peace-Athabasca Delta both experience transient wetland inundation, but with very different temporal and spatial patterns. Temporal stacking of inundation map time series finds that the transient wetland inundation is less extensive in the YF than in the PAD (Figures 6-9). Over the three-year study period (May 2017 to
Figure 11. (a) Differences in Yukon Flats monthly inundation frequency as estimated from Sentinel-1 SAR versus the Landsat-derived JRC product (Pekel et al. 2016), with enlarged areas (b) and (c). (d) Histogram presents pixel counts of monthly inundation frequency differences. Positive (negative) values signify higher (lower) monthly inundation frequency in Sentinel-1 relative to JRC. The pixel count of values agreements (difference = 0) in both products are not shown, due to its much larger value.

Figure 12. Open Water area, Inundated Vegetation area (including Aquatic Vegetation and Flooded Vegetation), and T5 threshold values for (a) descending, and (b) ascending Sentinel-1 orbits over the Yukon Flats study area. Time series in 2019 is shorter due to lack of Sentinel-1 coverage in May–July.
October 2019), the percentage of inundation area in the YF ranged from 10.7% to 12.1% in the YF, but from 18.0% to 19.0% in the PAD. Transient wetland inundation in the YF was ~102 km², totaling ~3.6% of the landscape, while that in the PAD was ~595 km², comprising ~9.1% of the landscape. We infer that methane emissions associated with transient wetland processes, for example, are thus most extensive on the PAD. Future work should consider integrating the time-series of maps produced in this study with process-based CH₄ models to estimate seasonal cycles in PAD methane emissions.

6. Conclusion

This study explores the utility of fusing Sentinel-1 C-band SAR data and Sentinel-2 MSI visible/NIR for tracking transient boreal wetland inundation in the Yukon Flats (Alaska, USA) and Peace-Athabasca Delta (Alberta, Canada). The resultant inundation maps were validated using contemporaneous independent in-situ field mapping (Kyzivat et al. 2021) collected as part of the NASA Arctic-Boreal Vulnerability Experiment (ABoVE). We found that most field-mapped wetlands were correctly detected in our satellite products, with overall classification accuracy for both study areas exceeding 90%. For both PAD and YF, the omission and commission errors are around 30% and 20%, respectively. Compared to a popular Landsat-based global surface water product (Pekel et al. 2016), the derived wetland maps are more sensitive to inundation beneath vegetation canopies, and superior in their spatial and temporal resolutions.

Our use of temporally varying radar backscattering statistics and a two-step decision tree further reduces false wetland detections. Because our approach uses both co-polarized (VV) and cross-polarized (VH) backscatter, it is sensitive to both double-bounce phenomenon through inundated vegetation (high co-polarized backscatter) and volume scattering from vegetation canopies (greater depolarization) (Marti-Cardona, Dolz-Ripolles, and Lopez-Martinez 2013; Townsend 2002). Similarly, phenological cycles of vegetation canopies, such as leaf and foliage loss, and ephemeral effects like wind/rain roughing of open surface water cause temporal and spatial variability in C-band SAR backscatter which complicates inundation mapping. The presented methodology mitigates these effects, by combining principles of dual-polarized C-band SAR backscatter, optical NDVI, and spatial adjacency.

Seven thresholds (Figure 3, Table 2) are needed to define decisions among the differing inundation components. Through statistical means, values for four of these thresholds (T1, T2, T5, and T7) are derived automatically, and three (T3, T4, and T6) are determined manually through trial and error. While the empirical values for T3, T4, and T6 determined here appear applicable to the Yukon Flats and Peace-Athabasca Delta, further study is needed to determine their applicability to other boreal regions.

The approach presented here has several limitations. First, it assumes that transient wetland inundation expands and contracts around permanent, open water bodies. Fully vegetated wetlands, such as bogs with no open water areas or fully vegetated marshes, are excluded from detection. As such, the approach is more specifically an open water and littoral zone (Kou et al. 2020; Kyzivat et al. 2022) wetland mapping methodology, rather than a general wetland mapping methodology. Second, due to the relatively short wavelength of Sentinel-1 C-band SAR, dense vegetation canopies cannot reliably be penetrated, causing an unknown amount of inundation to be missed under denser shrubs and/or forest (e.g. in Figure 4b). Both limitations thus render our wetland maps and area estimates (e.g. Figure 6–9) highly conservative. Unfortunately, we cannot quantify the errors embraced in the spatio-temporal inundation maps because the reported commission and omission errors are estimated using field observations, which are “one-off” in nature and therefore not available for every inundation map in the time series. Future work should consider utilizing longer wavelength satellite radar data, such as L-band SAR obtained by ALOS missions (e.g. Bourgeau-Chavez et al. 2017; Chapman et al. 2015; Evans et al. 2010; Ramsey, Rangeonwala, and Bannister 2013) and NASA-ISRO SAR Mission (NISAR) (Adeli et al. 2021), to expand the range of canopy densities through which inundation may be detected. Finally, to the best of our knowledge, no study has ever discerned Emergent Plants (EP) and Flooded Vegetation (FV) from SAR. Existing studies (e.g. Horritt et al. 2003; Tsyganskaya, Martinis, and Marzahn 2019; Sipelgas, Aavaste, and Uiboupin 2021) generally treated them as a same class. Our approach provides an exploratory delineation between EP and FV. However, it should be noted
that the boundary between them is not explicit enough. EP are classified as FV where their above-water structure induces a double-bounce effect, which may depend on water level. These same FV areas may be classified as EP if water levels rise sufficiently to submerge much but not all of their structure, which reduces the backscatter. Similarly, it is difficult to distinguish some Floating Plants (FP) and EP due to their similar backscatter characteristics. To mitigate this ambiguity, we create generalized maps combining these two categories (Figure 3). As compared with our original five-category classification, these generalized maps offer less inter-class confusion, but also less specificity with regard to detectable categories.

Despite these limitations, we conclude that the high temporal and spatial resolutions of Sentinel-1 SAR and Sentinel-2 MSI imaging enable effective monitoring of transient inundation patterns, both throughout the thaw season and interannually (e.g. Figures 6 and 8). Generation of geospatial inundation frequency maps over time (e.g. Figures 7 and 9) reveals that transient wetland inundation is less extensive in the YF than the PAD, with corresponding implications for transient wetland ecology, ecosystem services, and methane emissions. Time series of Sentinel-1 C-band SAR, screened with Sentinel-2 MSI optical imagery and validated with field observations, offer a valuable tool for tracking transient boreal wetland inundation.

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Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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This research was conceived by Chang Huang and Laurence C. Smith and developed by Chang Huang. Classification results were analyzed and interpreted by Chang Huang, Laurence C. Smith, Ethan D. Kyzivat, and Jessica V. Fayne. Christopher Spence contributed hydrological information; Ethan D. Kyzivat collected the training/validation database; Yisen Ming contributed validation support. Chang Huang and Laurence C. Smith wrote the paper. All authors participated in review and revision of the paper.

Data availability statement

The wetland training/validation data products used in this study are freely available at ORNL DAAC (https://doi.org/10.3334/ORNLDAAC/1883). The wetland inundation products developed in this study are freely available at ORNL DAAC (https://doi.org/10.3334/ORNLDAAC/1901). GEE codes and Python codes are available at the lead author’s GitHub page (https://github.com/chaunceyhuang1986/WetlandInundationByS1).

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