# A COMPARISON BETWEEN DIFFERENT SYNTHETIC APERTURE RADAR (SAR) SENSORS FOR WETLAND CLASSIFICATION

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## ABSTRACT

Wetlands are important natural resources which provide numerous advantages to the environment. They play a pivotal role in purifying water, controlling natural hazards, and conserving soil and water. Remote Sensing (RS) is a cost-effective and timely tool which has been long applied for wetland mapping/ monitoring. Furthermore, since the advent of Synthetic Aperture RADAR (SAR) sensors, they have been employed extensively in wetland classification. Due to their day-and-night, all-weather capabilities, their penetration depth, and their sensitivity to moisture, SAR sensors are valuable tools for wetland mapping and monitoring. Currently, there are several active sensors available which differ in terms of their wavelength, revisit time, and accessibility. Therefore, it is important to learn what sensor is more appropriate for wetland classification. This study is a comparison between various available sensors including ALOS PALSAR, ALOS-2, TerraSAR-x, and Sentinel-1 in terms of their potential for wetland mapping. The classification was carried out in both single temporal and multi temporal cases. Random Forest classifier was applied for the object-based mapping of the study area. The result of this study demonstrated that some freely available images including Sentinel-1 and ALOS PALSAR can yield comparable accuracies to that of RADARSAT-2 when combined with optical imagery. It is hoped that the result of this research can be applied in future operational wetland studies for better monitoring of these valuable natural assets.

**KEYWORDS:** Synthetic Aperture RADAR (SAR), Wetlands, Object-based, Classification

## INTRODUCTION

A wetland is defined as "land that is saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation and various kinds of biological activity which are adapted to a wet environment" (National Wetlands Working Group 1988). Wetlands provide many advantages to nature, including soil and water conservation, shoreline protection, reducing the risk of natural hazards, as well as benefits for humans such as aesthetic and recreational values (Grenier et al. 2007; Powers et al. 2012; Ji et al. 2015). Unfortunately, in the past the value of wetlands was unknown and wetlands were considered undesired. Consequently, wetlands have been drained extensively and have been supplanted with agricultural, industrial, and urban areas (Fraser and Keddy 2005; Gallant et al. 2007). Therefore, the requirement for continuous monitoring of wetlands is imperative, and the first step in monitoring is mapping.

Remote sensing, as a cost- and time-effective tool, has been applied in many studies of wetland mapping (see, for example, Chopra et al. (2001), Brisco et al. (2011), and Koch et al. (2012)). Amongst the different types of remote sensing images, Synthetic Aperture RADAR (SAR) images are assets for wetland monitoring due to their all-weather, day and night capability, and the ability to penetrate into the canopy (Hong et al. 2015). This type of image is especially useful when it is fused with optical imagery (Durieux et al. 2007; Bourgeau-Chavez et al. 2009). For example, Grenier et al. (2007) applied both RADARSAT-1 and Landsat images to classify wetlands on several scales. They started by classifying the wetland areas in the largest scale, and continued classification in a smaller scale after masking the classified parts. Similarly, Hong et al. (2015) applied different polarimetric decompositions extracted from TerraSAR-x along with RapidEye images to classify wetlands in Florida.

Random Forest (RF) is a classifier (Breiman 2001) which is commonly used for wetland mapping (Liu et al. 2016; Tian et al. 2016). RF includes a set of decision trees, each of which is constructed by applying a subset of training samples. The best split in each node is found using a subset of features. After the training process, a pixel or an object passes through each decision tree and the final class is assigned to the pixel/object using majority voting (Breiman 2001).

Object-based classification is clearly superior to traditional pixel-based classification, and has proved especially useful for wetland mapping (Benz et al. 2004; Powers et al. 2012; Dronova 2015).Equally important, since wetlands show a considerable amount of intra-annual change, multi-temporal investigations can be of great help (Ozesmi and Bauer 2002; Moser et al. 2016). Furthermore, for freely available datasets, acquiring multi-temporal images is convenient.

Therefore, in this study single-temporal classification was compared to multi-temporal classification. In this regards, the Avalon area has a variety of wetland classes which makes it ideal for wetland studies. Thereupon, the Avalon area was selected as the study area of this research.

Currently, there are several SAR sensors available that continuously acquire images, and there are millions of archived SAR images available, sometimes at no cost. SAR images exist in various bands and configurations, each of which is useful for the specific aspects of wetland studies. For example, L-band is very effective in detecting inundated areas beneath the vegetation canopy (Li and Chen 2005), and X-band is useful for distinguishing between various herbaceous vegetations (Henderson and Lewis 2008). Moreover, SAR images exist in different polarizarions of which full-polarimetric images are the most powerful for the purpose of wetland classification (Touzi et al. 2007; Marechal et al. 2012; Gosselin et al. 2014). Amongst the SAR imagery used in this research, RADARSAT-2 is the only full-polarimetric image available for the Avalon study area. Full-polarimetric images have high potential for wetland mapping/monitoring, because they can identify between different wetland/non-wetland classes. Many studies have obtained promising result using RADARSAT-2 (Touzi et al. 2007; Gosselin et al. 2014; Franklin and Ahmed 2017). Consequently, this study will compare the accuracy of classification obtained from RADARSAT-2 images versus other images in the Avalon study area. An optical image is used in conjunction with SAR images for two reasons: (i) to improve the accuracy of some classes such as the Urban class. (ii) to increase the number of available features, since using single-temporal, single- or dual- polarized data does not provide sufficient features to be included in the classification. Landsat imagery was selected for the study because it is available to users without any cost.

To recapitulate, the goal of this study is twofold: (i) to explore the capability of several types of SAR images for the purpose of wetland mapping in single-temporal and multi-temporal modes; and (ii) to explore if freely available images provide comparable levels of accuracy as the images that must be purchased. It is expected that the results of this study will assist researchers in choosing SAR images that best conform to their requirements in the best way, and contribute to the operational monitoring of wetlands.

# STUDY AREA AND DATASET

## Study Area

The study area is within the Avalon Peninsula, Newfoundland (NL), Canada, located approximately at 47˚27' N and 52˚52' W. The study area is within the Maritime Barrens ecoregion, which is dominated by balsam fir forests, heathland barrens, and urban and agricultural areas. Figure 1 shows the natural color composite of the study area.

## Field Data

The first phase of this research used Bog, Fen, Marsh, Swamp, and Shallow Water as wetland classes. High resolution aerial images were used to determine potential wetland areas. Then, a team of biologists explored some of the specified areas and classified them into one of the wetland classes defined by Canadian Wetland Classification System (CWCS) (National Wetlands Working Group 1997). Three non-wetland classes were also selected including

Urban, Upland, and Deep Water. Of the field data collected, 50 percent o were used for training and the remainder were used for testing classification accuracy.

**Figure 1.** The study area

**Table 1.** Specification of the images used in the study

| Sensor | Acquisition Date | Wavelength | Polarization |
|---|---|---|---|
| ALOS-1 | 2010/08/29<br>2010/10/14<br>2009/05/29 | L-band | HH, HV<br>HH, HV<br>HH, HV |
| ALOS-2 | 2015/08/02 | L-band | HH, HV |
| TerraSAR-x | 2016/08/11<br>2016/09/02 | X-band | HH<br>HH |
| Sentinel-1 | 2015/08/20<br>2015/06/25<br>2015/07/31 | C-band | HV, VV<br>HH, HV<br>HH, HV |
| RADARSAT-2 | 2015/06/10<br>2015/08/21 | C-band | HH, HV, VH, VV<br>HH, HV, VH, VV |
| LandSAT-8 | 2015/08/15 | | |

## Remote Sensing Imagery

The SAR images used in this study are taken from ALOS PALSAR, ALOS 2, TerraSAR-x, Sentinel-1, and RADARSAT-2 sensors. Advanced Earth Observation Satellite Phased Array type L-band SAR (ALOS PALSAR) was a Japanese earth observation satellite which stopped working on May 2011. Naturally, the available ALOS PALSAR images for the study area are outdated relative to the other images used in the study, but they were applied because of the two following reasons: (i) ALOS PALSAR was performing in L-band; and (ii) Currently, there is a rich archive of the images acquired by ALOS PALSAR at no cost. ALOS-2 was launched in 2014 as a follow-on of ALOS PALSAR although images from the former are not free. TerraSAR-x, a German satellite which was launched in 2007, acquires imagery in X-band in different modes and polarizations. Sentinel-1, launched in 2014, provides users with free C-band images available in single and dual-polarized modes. RADARSAT-2, launched in 2007, acquires C-band SAR images in a variety of modes. For this study area, quad-polarized images were available from RADARSAT-2. The specifications of the images acquired by each sensor are depicted in Table 1.

## METHOD

Object-Based Image Analysis (OBIA) was applied in this paper. Most often, segmentation of SAR images does not yield acceptable results as a consequence of the presence of speckle. Therefore, only Landsat-8 was segmented using multi-resolution algorithm, and the result was used for both optical and SAR data. eCognition™ software was used for this purpose, which resamples all the images to a common resolution before classification. For the Landsat image, the mean of all bands were used. For all SAR imagery, the mean of intensity in the available polarization was applied. For RADARSAT-2, other elements of covariance and coherency matrices, and the Freeman Durden decomposition (Freeman and Durden 1998) and the Cloude-Pottier decomposition (Cloude and Pottier 1997) parameters were also utilized. All these elements were examined for classification and the best combination of the feature sets with the Landsat image was finally selected. Then, the Random Forest classifier was applied on the object-based features. For each of the datasets classification was carried out in both single-temporal (using the highlighted date only) and multi-temporal (using all available dates) ways. The exception was ALOS-2, for which images from another date were unavailable. Finally, accuracy assessment was carried out using test samples.

## RESULTS AND DISCUSSION

Figure 1 shows the result of classification for both single-temporal and multi-temporal cases. The accuracy is presented in terms of the overall accuracy, the average wetlands' producer accuracy, and the average wetlands' user accuracy. For simplicity, Landsat will not be mentioned in the classification combination in the following discussion, as it is common amongst all classification combinations.

In the first step, comparison can be made amongst all single-date images excluding RADARSAT-2. The overall accuracy is more or less the same for Landsat combination with ALOS PALSAR, ALOS-2, TerraSAR-x, and Sentinel-1. TerraSAR-x has provided the highest overall, the wetlands' average producer, and the wetlands' average user accuracies. This is interesting because TerraSAR-x image is the only single-polarized image for this study area. However, the reason is most probably due to the fact that TerraSAR-x has the highest resolution (~ below 4m) which conforms to the small size of the training samples in this area. Another reason for the high accuracies may be a result of the wavelength of TerraSAR-x image (X-band) which helps in the discrimination of herbaceous wetlands. After TerraSAR-x, ALOS PLSAR produced the highest wetland accuracy, while ALOS-2 yielded the lowest accuracy. The main difference between ALOS PALSAR and ALOS-2 is the acquisition date. ALOS PALSAR has been acquired on August 2010, whereas ALOS-2 has been acquired in August 2015 (almost the same acquisition date as Landsat). Applying ALOS PALSAR has caused the intra-annual changes of wetlands to be considered, and that is may be the reason of the accuracy improvement. The fact that Sentinel-1 has not produced accuracies as good as those of ALOS PALSAR can be the acquisition date of Sentinel-1 which is close to that of Landsat-8.

Amongst the multi-date classifications excluding RADARSAT-2, ALOS PALSAR yielded the highest accuracy. Multi-date TerraSAR-x classification, however, resulted in the least accuracy. Although many studies have reported that multi-temporal classification is very useful for wetland studies (Ozesmi and Bauer 2002; Li and Chen 2005), it is also important to select the appropriate acquisition date (Henderson and Lewis 2008; Bourgeau-Chavez et al. 2009). For example, in this study, using images from different acquisition dates has slightly increased the accuracy in cases of ALOS PALSAR and Sentinel-1 (if all three types of accuracy are to be considered). In the case of TerraSAR-x, however, the accuracy has decreased. From the two TerraSAR-x images used in the multi-date classification, one has been acquired in September. On that date, probably both wetlands and non-wetlands are more wet as it is the beginning of fall, and the X-band wavelengths is too short to penetrate through the wet canopy and identify the type of vegetation to distinguish wetlands from non-wetlands. That may be the main reason for the reduction in the accuracy.

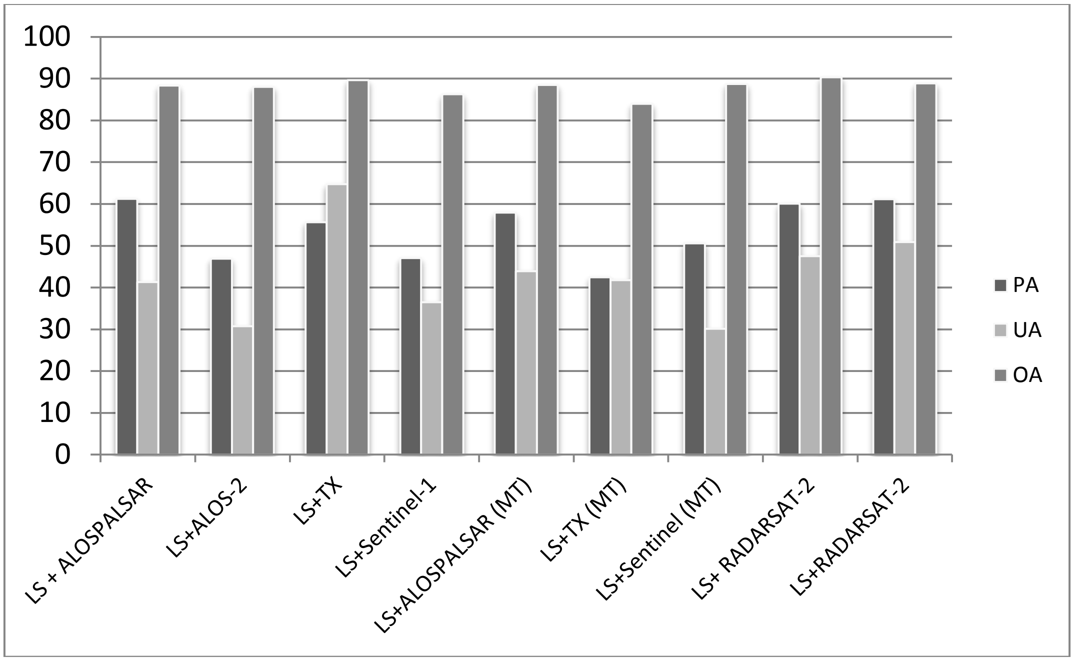


**Figure 2.** The overall, the average wetlands producer, and the average wetlands user accuracies for classification using Landsat (LS) plus the images from various sensors. (TX=TerraSAR-x, MT=Multi-date)

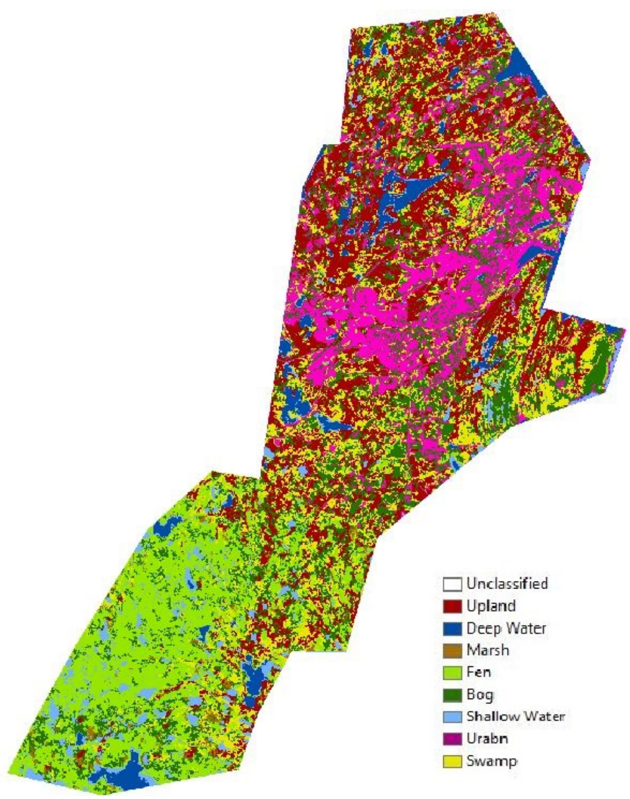


**Figure 3.** The classified image from the study area using Landsat-8 and TerraSAR-x

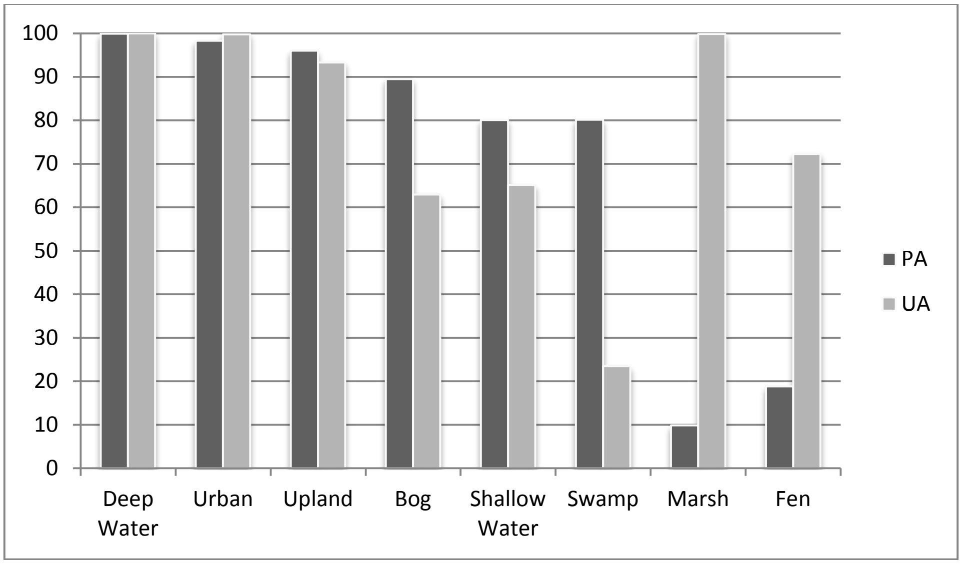


**Figure 4.** Class-based producer and user accuracies for classification using Landsat-8 and TerraSAR-x

RADARSAT-2, in both single-date and multi-date cases, has performed better than or as well as all other images, with the exception of TerraSAR-x, which has performed better in terms of wetlands' average user accuracy. This was expected because, as mentioned previously, RADARSAT-2 images are full polarimetric and are naturally more powerful than single- or dual- polarized images. Additionally, using multi-temporal RADARSAT-2 images has caused an increase in the wetlands' average user and producer accuracies when compared to the single-date classification, although a slight decrease in the overall accuracy can be also observed.

Overall, Figure 2 is promising because it shows that freely available images can yield comparable accuracies to RADARSAT-2 which is full-polarimetric and has to be purchased. However, one should keep in mind that this is only one case study, the results of which could be contingent on many factors, and more research is needed for drawing a robust conclusion.

Figure 3 and Figure 4 show the classified image using Landsat-8 plus TerraSAR-x (single date) and the class-based accuracies, respectively. When the classified image is compared visually to the image of study area (Figure 1), it can be observed that several classes have been identified with an acceptable accuracy. However, according to Figure 4, there is a high confusion in some wetland classes such as Swamp, Marsh, and Fen.

## CONCLUSION

This study attempted to compare the result of wetland classification using various Synthetic Aperture RADAR (SAR) images. RADARSAT-2 was superior to the other sensors in terms of accuracies except for TerraSAR-x for which the user accuracy was higher than that of RADARSAT-2. Excluding RADARSAT-2, in the single-temporal case TerraSAR-x image yielded the best results, while in the multi-temporal case ALOS PALSAR performed well. The results of this research are promising and illustrate the possibility of using freely available images instead of those which must be purchased. However, it should be considered that the obtained results are only for one study area and more research is needed for drawing a more robust conclusion.

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