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Integration of high-resolution multitemporal satellite imagery for improving agricultural crop classification: A case study

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Abstract. Timely and accurate agriculture information is vital for ensuring global food security. Satellite imagery has already been proved as a reliable tool for remote crop mapping. Planet satellite imagery provides high cadence and global satellite coverage with higher temporal and spatial resolution than the Landsat-8 and Sentinel-2. This study examined the potential of utilizing high-resolution multitemporal imagery along with and normalized difference vegetation index (NDVI) to map the crops in Prince Edward Island, Canada. Multitemporal Planet imagery at 3 m resolution combined with multitemporal NDVI data was used as inputs to the Support Vector Machine (SVM) algorithm. The accuracy of crop mapping by SVM increased with the use of multitemporal NDVI data combined with Planet satellite multitemporal imagery. The framework developed based on Planet imagery in this study is applicable for large-scale implementation across Canada and other regions of the world for accurate crop mapping.

Keywords.
Planet satellite imagery, 3 m resolution, Normalized difference vegetation index, Support Vector Machine

1. Introduction

Remote sensing, in combination with geographical information systems (GIS), and machine learning algorithms, is commonly used in agricultural monitoring applications such as crop mapping, crop water demands calculation, etc. Remote sensing in conjunction with machine learning algorithms is considered a reliable technique to produce crop maps at higher accuracy Produced maps at a higher resolution are more beneficial to prepare the up-to-date crop inventory for better decision making such as implementing by-laws of cover rotation (Kussul et al., 2016). Nowadays, higher temporal and spatial resolution imagery is easily accessible due to the new Planet satellite (Cheng et al., 2020). Planet imagery has already been used to detect crop sowing, field boundaries, agronomic parameters, and crop mapping in China's Jiangsu province (Cheng et al., 2020). The novelty of the current study is that it uses consistent ground truth data, and Planet satellite (3 m resolution) imagery in conjunction with Support Vector Machine (SVM) learning algorithms to map crops in PEI, Canada.

2. Material and methods

2.1 Study area

Prince Edward Island (PEI) is an agriculturally dominated province located in Canada. The Island is centred between 46.5107° N 63.4168° W and is subdivided into three counties (i.e., Prince, Queens, and Kings. The major crops of this Island are forage, barley, oat, spring wheat, corn, canola, soybeans, potato, and blueberry. The devoted land area for significant crops is 85,500 for potatoes and 17,6000 ha for corn, wheat, barley, and soybeans (Department of Agriculture and Land, 2020). Three-year crop rotation is written into the agriculture crop rotation act to avoid the over the planting of row crops to maintain soil health. To monitor the crop rotation act, crop maps prepared at a higher resolution will prove helpful to enforce this policy.

2.2 Field data/ground truth data

The ground truth data for training and validation of machine learning algorithms were acquired through a field campaign in the summer of 2020 during the crop growing season. Land cover and crop type classes with latitude and longitude coordinates were recorded using a handheld Garmin ETREX 22X GPS unit (Garmin Ltd, Kansans, USA) with an average accuracy of 3 m. The final output of this process was a CSV file gathering 2000 coordinates for urban, forage, barley, oat, spring wheat, corn, canola, soybeans, potato, and blueberry across PEI.

3. Support vector machine algorithm

A support vector machine is a supervised machine learning algorithm used for classification and regression purposes (Mustafa et al., 2017). Multitemporal Planet imagery stand-alone (data set A) and in combination with normalized difference vegetation index (NDVI) (data set B) was used as input in SVM to evaluate if adding NDVI improved the classification accuracy. The classification with the SVM has been performed using the ArcGIS Pro classification wizard. The collected ground truth data were randomly split into 80% and 20% sections for the training and validation of SVM. To achieve higher classification results from SVM, the parameter is set by the trial-and-error method number of samples per class (200) (Onojeghuo et al., 2018).

4. Results

The SVM hit the acceptable user accuracy and producer accuracy for each class, namely, barley, blueberry, oat, canola, corn, forage, potatoes, soybeans, spring wheat, and urban of 72 to 90% when stand-alone multitemporal Planet imageries were utilized as an input data source. The F1 score yielded by urban, forage, barley, oat, spring wheat, corn, canola, soybeans, potato, and blueberry were 65, 93, 81, 85, 82, 89, 87, 79, 86, and 89, respectively. The multitemporal Planet imagery in conjunction with SVM-based classified maps achieved an overall accuracy of 83.8% and a kappa coefficient of 82%. The producer accuracy, user accuracy, kappa coefficient, overall accuracy, and F1 increased significantly when multitemporal Planet imagery was combined with multitemporal NDVI data and used as the input data source in SVM. A 6.25% increase in overall accuracy and a 7% increase in kappa coefficient value were observed. The user accuracy increased for urban, oat, spring wheat, corn, canola, soybeans, potato, and blueberry, 13, 8, 12, 8, 7, 15, 5, and 5 % respectively, when multitemporal NDVI data was combined with multitemporal Planet imagery. The F1 score of each crop type also increased except for forage. The compared result of SVM for both input data sets (i.e., multitemporal Planet imagery stand-alone data set A, multitemporal Planet imagery fused with multitemporal NDVI-data set B) proved that multitemporal Planet imagery fused with multitemporal NDVI is a better input data source for increasing the mapping accuracy and prepared map for both data sets are represented in Figure 3 A, B.

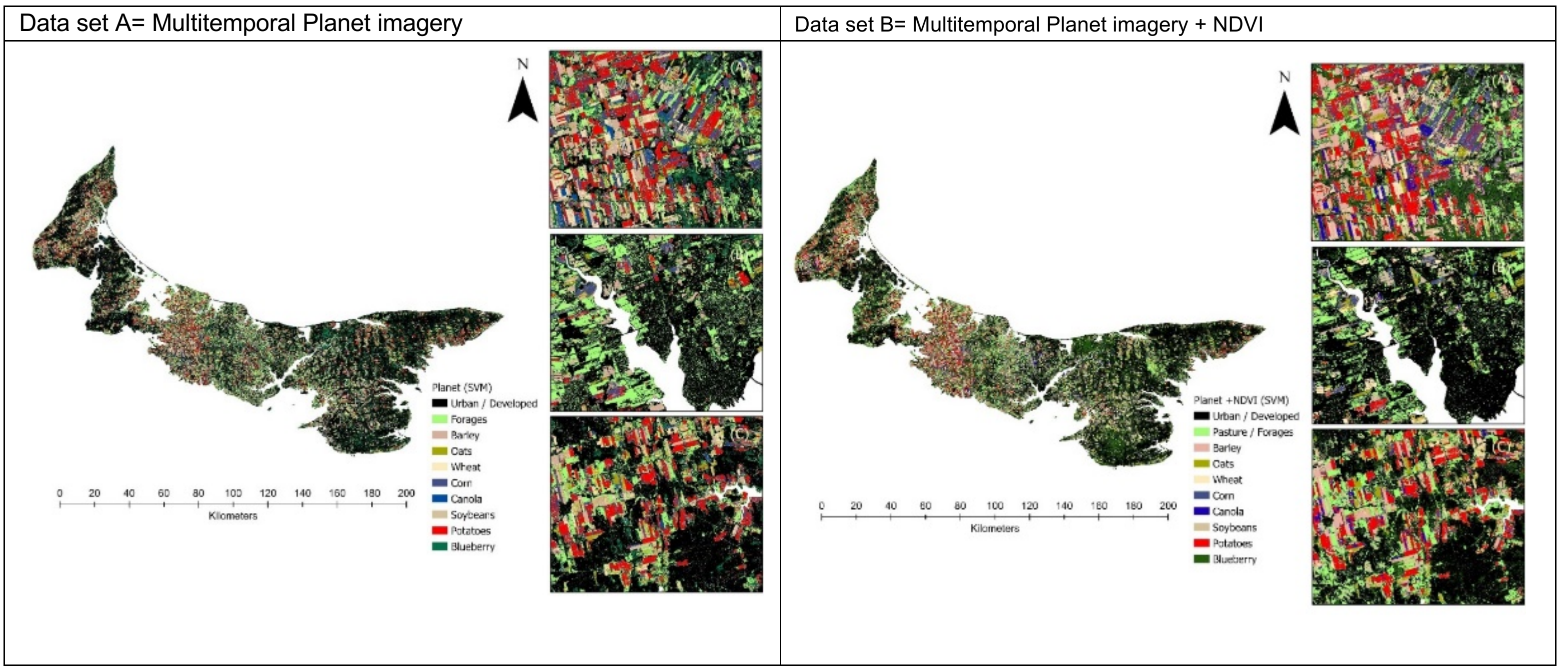

Figure 3(A). Support vector machine-based classified maps using only multitemporal Planet imagery. (B). Support vector machine-based classified maps using multitemporal Planet imagery combined with multitemporal Planet imagery.

5. Conclusion

The results point out that the SVM algorithm mapping accuracy increased when combined multitemporal Planet imagery and multitemporal NDVI data source were used as an input. This approach achieved the overall accuracy and kappa coefficient of 90 and 80% respectively. These results can help produce higher accuracy and higher resolution crop maps for any area, which helps make the agriculture policy, acreage estimation, and decision-making. This study is at a preliminary stage, further research will compare these two data sets in the different machine learning algorithms.

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