Towards the Creation of a Canadian Land-Use Dataset for Agricultural Land Classification

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ABSTRACT

Monitoring the land-use and land-use change in perennial, annual and cover crops with remote sensing (RS) can help agronomists and agricultural agencies to improve management and address issues related to climate change, global food security and biodiversity monitoring (Mazzia et al., 2020). The surge of open-access RS image data is leading to an incredible increase in research opportunities, while simultaneously empowering agronomists with data-driven tools. Specifically, RS has played an integral role in the field of land cover classification (Weiss et al., 2020). However, most studies attempting pixel-wise or patch-wise classification of RS imagery are done with a single reference image. This limits the ability to generalize the insights gained from a particular study and extrapolate them at a larger spatial or temporal scale (Khatami et al., 2016). Therefore, there is a need for a standardized, accessible dataset that would allow the creation of scalable models, and that would facilitate reproducibility and transfer learning on similar tasks (Helber et al., 2018).

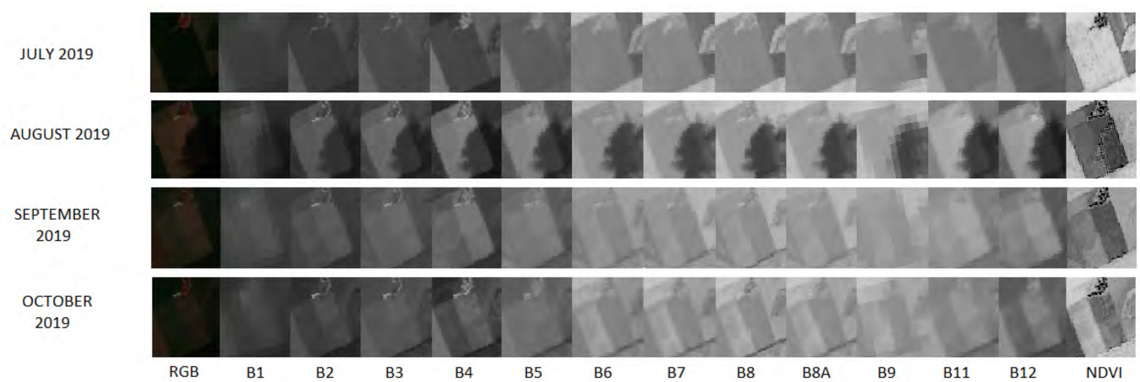

Figure 1: Example of a Sentinel-2 dataset for a barley field in Ontario, Canada. The mosaic shows the different reflectance bands (B1 to B12) present in the median image for each month.

In this study, a novel patch-based dataset, inspired by the *Eurosat* dataset (Helber et al., 2018), was compiled using optical satellite images of Canadian agricultural croplands retrieved from Sentinel-2. A total of 5,000 high-resolution (10 x 10 m) geo-referenced images of 10 crop types (soybeans, corn, sorghum, oats, millet, barley, potatoes, pasture and forages, mixed wood, and apples) were collected over 4 distinct seasonal periods. The scenes were extracted using the Google Earth Engine tool (Gorelick et al., 2017) and were manually labelled using the Canadian Crop Inventory (Agriculture and Agri-Food Canada, 2016). The images contained all the sentinel spectral bands with the addition of precalculated vegetation indices such as NDVI, GNDVI and PSRI (Figure 1). Using a ResNet-50 architecture, we assessed classification accuracy on this dataset over multiple growing seasons and environmental conditions. Finally, the classification error (agricultural land vs. others) between this dataset and the *EuroSat* dataset was evaluated. Based on these results, the workflow and dataset developed proved to be a first step toward a better classification of North American land cover.

***Keywords*—** Precision agriculture, cropland, remote sensing, image classification, deep learning.

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