Mapping Canada’s Rangeland and Forage Resources using Earth Observation

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Introduction
Differentiating rangeland, pasture and forage crops using Earth Observation (EO) is generally difficult because of their spectral reflectance similarities and partly as a result of the variability of climate, soil type and management practices. This variability becomes increasingly problematic over larger areas. Previous efforts to create an inventory of rangeland and forage resources across the Canadian Prairies using classification of EO data have not achieved desired accuracies. The objective of this research is to determine which variables derived from remote sensing (optical, SAR or both) and the acquisition timing during the growing season can be most effectively used to produce increased classification accuracy of Canada’s forage resources. Results to date will be presented.

Materials & Methods

Two pilot sites were selected which represent the variability of climate, soil, and ecoregions across the Canadian prairies. The first pilot site is located in the Aspen Parkland ecoregion of Southwestern Manitoba. The second site is located in the mixed grassland ecoregion of Southern Alberta. Field data related to land cover type and dominant species composition were collected across each pilot site during the 2015 growing season using a GPS-enabled ArcPad tablet. Additional reference data were acquired from provincial crop insurance datasets.

Due to the costs associated with acquiring a high resolution EO dataset for the prairie region, data sources were limited to cost-effective optical data and SAR as the results of this study may eventually be incorporated into an operational framework. Two sources of EO data were used to examine the potential of optical multispectral data as well as the applicability of available SAR data. Landsat-8 images were obtained from the US Geological Survey. All available 1T (terrain corrected) imagery with limited cloud/haze cover was obtained for the 2015 growing season over both study sites. The Landsat-8 scenes were radiometric and atmospherically corrected using the ATCOR 2 algorithm (Richter, 2010). Three or four scenes were used in the final classification for each site as images were reduced to those of acceptable quality, i.e. with no residual haze or clouds effects (Table 1). At each site a pre-crop greening and mid growing season scene were available, for the Manitoba site a late fall image was available after all crops had been harvested. Several studies have shown that C-band SAR data have proved to increase final map accuracy of agricultural classifications when used alone or in combination with optical data (McNairn et al., 2009; Smith and Buckley, 2011). Because of the visible difference in plant structure observed between rangeland, cropland and forage cover types, Radarsat-2 wide beam mode dual polarization imagery, acquired in July, 2015 and then resampled to 30m pixel spacing, was used in addition to Landsat-8 optical data.
Due to the limitations of the spatial resolution of available optical and SAR data and based on initial classification tests of detailed classes, reference data were aggregated into three broad classes of rangeland, seeded forage, and cropland. All non-agricultural land was masked out using an existing AAFC dataset. The rangeland class is comprised of cover types such as upland native grassland, upland non-native grassland, reverted pasture, meadow and native shrubland. The seeded forage class aggregated perennial pasture and hay, as the two were determined to be indistinguishable at the spatial and temporal resolution required for the study. All annual crops were aggregated into one cropland class.

In addition to atmospherically corrected optical data, vegetation indices were derived from Landsat-8 multispectral bands. They included vegetation indices which highlight productivity and phenological differences in land cover types such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Senescent Vegetation Index (NDSVI), an indicator of the amount of senescent vegetation; and Tasseled Cap Wetness (TCW), which responds to soil and vegetation moisture. The potential of these variables was assessed in subsequent classifications.

Although there are many available pixel-based unsupervised classification algorithms, the random forest (RF) classifier was chosen for this study (Breiman, 2001). RF is a machine learning classifier which has shown improved results over more traditional classifiers such as maximum likelihood and other decision tree classifiers (Sonobe et al., 2014). RF was selected because it does not depend on parametric data, can be used with large numbers of variables, and it produces analyses of variable importance and internal classification error (the out-of-bag (OOB) error). An independent accuracy assessment was also conducted for each classification. Several classifications were run using logical groups of variables and the performance of classifications were compared using overall accuracy.

Results & Discussion
Several tests were conducted to determine which combination of optical and SAR variables produced the highest overall class accuracy. The first classifications were run using the Landsat multispectral data for all combinations of one, two and three dates (spring, summer, and late summer/fall). Generally, overall accuracies were improved when two or more dates were used. Ideally three dates should be used, representing pre-crop greening, mid growing season, and post-harvest, respectively. The addition of SAR to the optical variables increased accuracy for both the rangeland and seeded forage classes; however, a significant improvement was not shown for the cropland class for either site. The use of phenological variables derived from three dates of NDVI as well as three other vegetation indices improved classification results when compared to using only multispectral bands as optical variables. Again, using two or more dates significantly improved accuracy over using variables from a single date. The stability of the RF classifier was tested by reducing variables to the top ten and top five as determined when all available variables were included in a classification. The RF variable importance measure was used to reduce the number of unimportant and correlated variables (Breiman, 2001). Variables derived from spring imagery were determined to be the most important for distinguishing between rangeland and forage, specifically TCW and NDVI. Additionally, NDSVI, the indicator of senescence in late summer, was an important variable for all classes.
Conclusions & Implications
Knowledge-based variables including vegetation indices derived from optical imagery have the potential to increase classification accuracy for rangeland and forage classes over the use of multispectral band reflectance alone and in combination with backscatter values derived from SAR. With this knowledge, steps can be taken to improve the accuracy of existing EO-based inventory products to better monitor Canada’s rangeland and forage resources at a national scale.

References


