AAFC Annual Crop Inventory: Status and Challenges

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Introduction

The Earth Observation Service (EOS) at Agriculture and Agri-Food Canada (AAFC) offers a source of high quality, timely and accurate data and expertise based on satellite based and in-situ earth observations, to address the sectors policy and program needs. Understanding the state and trends in agriculture production is essential to combat both short-term and long-term threats to stable and reliable access to food for all, and to ensure a profitable agricultural sector.

Starting in 2009, EOS began the process of generating annual crop type digital maps. Focusing on the Prairie Provinces in 2009 and 2010, a Decision Tree (DT) based methodology was applied using optical and radar based satellite images. For the 2011 growing season and future years, this activity is extended to other provinces in support of a national crop inventory. So far, this approach can consistently deliver a crop inventory that meets the overall target accuracy of at least 85% at a final spatial resolution of 30m.

Crop Mapping Methodology

For operational purposes, AAFC needs a crop classification system that is efficient, economic, stable and repeatable, and one that can handle a large data volume capacity. The classification can be broken down into 7 generalized steps that are required to produce a digital crop type map (Fig. 1).

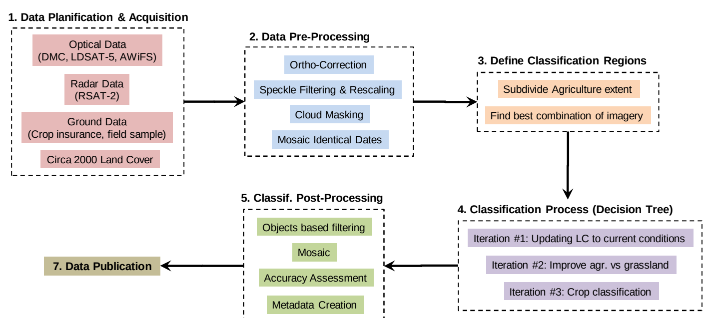

Figure 1. Crop type mapping flowchart

Successful crop identification relies on image acquisitions from multiple sensors during key crop phenological stages (reproduction, seed development and senescence). Multi-temporal optical data are the primary data source for crop classification because the NIR/SWIR channels are vital to crop classification. Over a growing season, at least 3 optical images are required to successfully identify crops. SAR images improve the overall accuracy, especially when some optical data is not acquired. To reduce file sizes and processing time, the agricultural extent is subdivided into more manageable regions (Fig. 2). Region files are classified individually with training data from various sources.

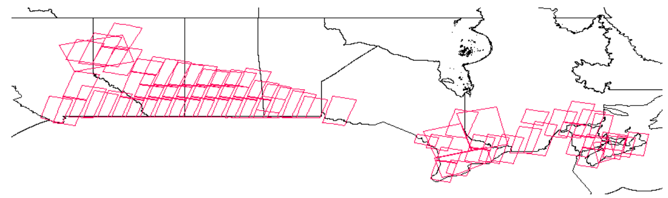

Figure 2. Division of the 2011 agricultural extent of Canada into regions.

The DT method, as implemented in see5 software, is a multivariate model based on a set of decision rules defined by combinations of features and a set of linear discriminant functions that are applied at each test node. Decision boundaries and coefficients for the linear discriminate function are estimated empirically from the training data.

In order to improve accuracy (up to 5%) and aesthetics, an eCognition segmentation and majority filter were applied to the DT classification. This assigned the majority class value within each object primitive to the entire polygon. Filtered classified regions were then merged together through an automated mosaic process that prioritizes areas with higher accuracies.

2011: First National Crop Map

Optical satellite data from the DMC constellation were used in combination with Landsat-5 and Radarsat-2 images to complete the 2011 classification, which was expanded to cover all Canadian provinces with the exception of Newfoundland (Fig. 3). This inventory was completed at an overall mapping accuracy of 85%.

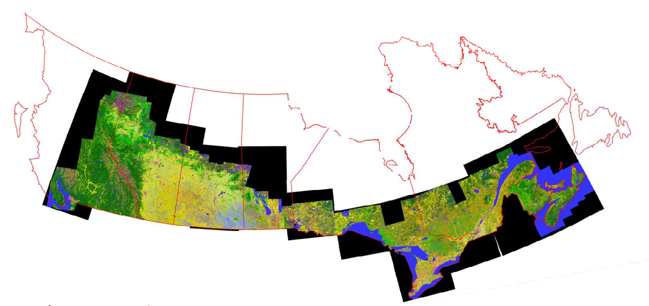

Figure 3. The 2011 crop inventory.

The value of this product is wide ranging and provides fundamental information on the state and changes in the agricultural landscape. For example, excessive wetness has been a reoccurring issue for Canadian agriculture, particularly in recent years. The 2011 annual crop inventory map generated for the Canadian Prairie Provinces was used to generate a map of acreages that were too wet to seed in the spring of 2011. The acreages were found to be within 3% of the independent estimates provided by the Provinces.

Future Direction

Crop maps are typically delivered 8 months following the end of growing season (Fig. 4). To satisfy existing and potential new users, the product should ideally be made available by September or even within the growing season as an estimated inventory.

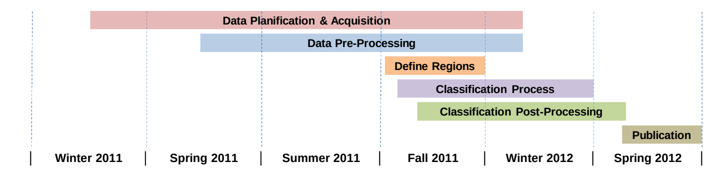

Figure 4. 2011 Crop Mapping Timeframe.

To resolve this issue, EOS staff will implement a new and fully automated crop classifier that should significantly reduce production time. As a major upgrade, classification regions will be defined automatically based on images extent, cloud coverage, training site distribution and preliminary accuracies. In addition to reducing analyst intervention, it will also optimize product accuracy. In 2012, the lack of affordable optical data will force AAFC to rely mostly on RSAT2 observations (Fig. 5). This brings new challenges, given a doubling of the number of images as compared to 2011. Over the next 2 years, modifications to our classification system will be made to ingest and process new satellites data such as Radarsat Constellation Mission (RCM), ESA's Sentinel and Landsat Data Continuity Mission (LCDM).

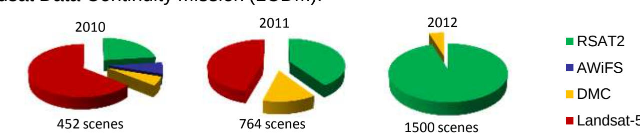

Figure 5. Number and type of images used for classification between 2010 and 1012.

Recently, new classifier algorithms, such as the Random Forest (RF) classifier, have become available. When compared to our traditional DT classifier, the RF classifier delivered several advantages: (i) overall and class specific accuracies were generally higher, (ii) a supplementary variable importance measure was provided and (iii) in tests of the classification speed, the RF outperformed the DT by classifying 18 times faster[1]. The RF classifier will be tested in our semi-operational environment in 2012.

Significant headway needs to be made in methods development for the annual crop inventory. This includes new approaches for assimilating and processing the unprecedented volume of EO data required to map nationally, and the development of new classification methodology, increasing product accuracy, and significantly reducing the delivery time of the final product.

Reference

[1]B. Deschamps, H. McNairn, J. Shang, X. Jiao. 2012. Towards operational radar-only crop type classification: comparison of a traditional decision tree with a random forest classifier. Canadian Journal of Remote Sensing, 2012, 38(1): 60-68.