EARLY-SEASON CROP CLASSIFICATION WITH RADARSAT-2 POLARIMETRIC SYNTHETIC APERTURE RADAR IMAGERY

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ABSTRACT

Timely crop classification maps are essential for the agriculture sector to ensure food security and understand the state and trend of crop growth. Though there are several crop monitoring systems in operation, early-season crop classification is still in demand. We developed a robust crop growth estimation technology previously with synthetic aperture radar (SAR) imagery for canola in Canadian Prairies, and we are extending the procedure to enable accurate early-season crop classification. Here we present a dynamic crop classification technique with RADARSAT-2 (RS2) polarimetric SAR (PolSAR) imagery for the classification of canola, corn, soybean and wheat, the four major crop types in Canadian Prairies. The procedure achieved over 90% classification accuracy of the major four crop types in the testing area by the end of July.

Index Terms— Agriculture, crop classification, synthetic aperture radar, RADARSAT-2

1. INTRODUCTION

Timely and accurate crop monitoring is an essential need for Canada as one of the largest producers and exporters of agricultural products in the world. Remote sensing has been the indispensable tool for such task and current annual crop inventory (ACI) are produced by Agriculture and Agri-food Canada (AAFC) at end of each season. However, more timely and accurate crop inventory information is still in demand for monitoring and prediction purposes. This study aims to produce a system to generate crop classification maps as early as possible in growing seasons to support better decision-making for the government and the industry.

Most successful crop classifiers utilize all-season data, especially mid-season and late-season. Example literature in [1, 2, 3, 4] used multi-temporal images from both electro-optical data and multi-polarization SAR images at different frequency bands to classify different crops. Around 90% accuracy for different types of crops can be achieved if mid-season and end-season data is available.

Early season crop classification is more challenging as most crops have similar reflectance patterns until certain growth stages. In [5] a mapping procedure to discriminate winter crops from spring/summer crops was developed without differentiating individual crop types. [6] studied early-season classification of corn, soybean and pasture-forage using both RS2 and TerraSAR-X (TSX) data. Results showed TSX can deliver accurate maps of corn and soybeans (above 85% accuracy) by end of June. Current studies on early-season classification are still limited to using one season of data or limited crop types. In addition, observed frequent cloud coverage in spring would limit the availability of optical satellite images, so that SAR sensors could potentially deliver crucial information for early-season classification.

One of the factors affecting crop phenological development is the accumulated heat over the growing season. Without extreme conditions such as drought, flood or disease, the accumulated heat is directly affected by temperature. This causes large year-to-year and region-to-region variations in calendar dates of crop growth stages. In this project, accumulated heat, represented by Growing Degree Days (GDD), is used instead of calendar days to make the product cross-year and cross-region compatible. The method has been proven effective in predicting growth stages of canola and it's cross-region and cross-season compatible in our previous research [7]. We are extending this method to other crop types to enable successful early-season crop classification.

2. DATA AND STUDY AREA

The proposed study areas (SA) are in the Prairie Provinces in Canada are: Carman, Manitoba (SA1), Red deer, Alberta (SA2) and Rosthern, Saskatchewan (SA3), with similar topography but different crop seasoning. The data for developing the algorithm include archived RS2 quad polarization (quad-pol) images in SA1 in previous Soil Moisture Active Passive Validation Experiment (SMAPVEX) campaigns in 2012 and 2016, as well as acquisitions in 2014 and 2017. RS2 quad-pol images in SA2 and SA3 were acquired from the archives. There are 10, 4, 75 and 20 scenes in SA1 in

Table 1. RS2 polarimetric features

Features	Details
Cloude-Pottier decomposition [9]	Alpha, Beta, Delta, Gamma, Lambda, Entropy, Anisotropy
Reflectivity ratios	$S_{HH}/S_{HV}, S_{HH}/S_{VV}, S_{HV}/S_{VV}$
Differential reflectivity ratios	$(S_{HH}-S_{VV})/S_{VV}, (S_{HH}-S_{HV})/S_{HV}, (S_{HV}-S_{VV})/S_{VV}$
Alternative polarimetric parameters	Conformity coefficient, Scattering predominance, Scattering diversity, Degree of purity, Depolarization index

S_{HH} denotes the intensity of the horizontal transmit and horizontal receive (HH) polarization, S_{VV} denotes the intensity of the vertical transmit and vertical receive (VV) polarization, S_{HV} denotes the intensity of the horizontal transmit and vertical receive (HV) polarization

2012, 2014, 2016 and 2017, respectively, plus 24 and 12 scenes in 2017 for SA2 and SA3, respectively. Field observations of crop growth stage data was provided by AAFC during the above period. Corresponding daily weather data at nearest weather stations was acquired from the Government of Canada. The ground truth of the classification was collected from ACI maps produced by AAFC [8] in 2017.
In this study, we used all RS2 images and the corresponding crop growth stage data to produce growth stage models for canola, corn, soybean and wheat. Since the data from SA2 and SA3 does not have all four crop types, SA1 in 2017 was used as validation site to compare with ACI maps.

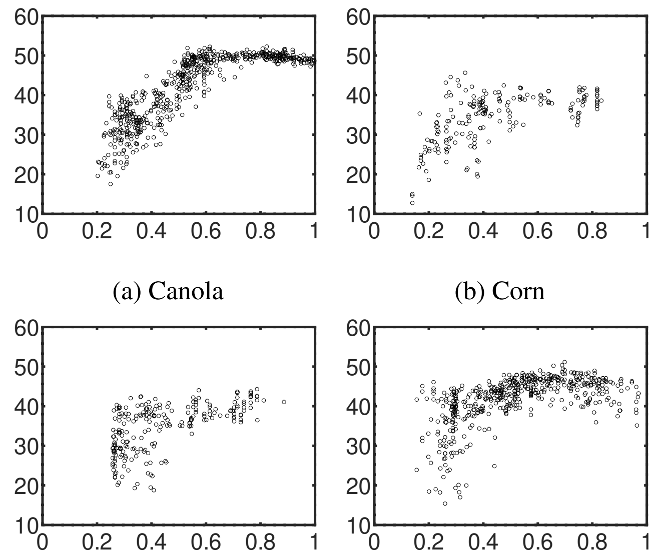
3. METHOD

3.1. Data Preprocessing

The RS2 quad pol images were first preprocessed with a refined Lee filter, and 18 polarimetric features were derived. The RS2 polarimetric features are listed in Table 1. Afterwards, polarimetric features were extracted from all images per field with crop growth stage information. The RS2 features were summarized per field using the median values.
The crop growth stages were recorded in the format of Biologische Bundesanstalt, Bundessortenamt und CHemische Industrie (BBCH) scales, where number presents particular growing stages. The BBCH values are continuous, so that BBCH to standard cumulative GDD mappings was created for each crop with reference to literature. With the mappings, BBCH values could be translated to a continuous variable.

3.2. Feature Modelling

Since each crop need different GDDs to mature, we use a normalized state variable called maturity for feature calibration and modelling. Crop maturity is in the interval $[0, 1]$ and



(a) Canola (b) Corn

(c) Soybean (d) Wheat

Fig. 1. Feature response models of four crops (X axis: crop maturity, Y axis: alpha angle

it changes linearly with GDD:

$$Crop\ Maturity(n) = \frac{\begin{array}{c}Avg.\ GDD\ crop\ to\ reach\\ BBCH\ n\ from\ seeding\end{array}}{Avg.\ GDD\ crop\ lifetime} \quad (1)$$

Feature selection was performed to evaluate most effective RS2 features in the crop fields. Maximal Information Coefficient (MIC) [10] was used as a measurement of dependency between features and crop maturity. The selection criteria were each selected feature should have a moderate dependency with crop maturity and not exhibit high dependency with each other. The selected RS2 features are alpha angle, anisotropy, beta, delta, lambda from the Cloud-Pottier decomposition [9], reflectivity ratio HH/HV, and reflectivity ratio HH/VV. With beam mode compensation, GDD calibration and noise filtering, crop growth models for each crop were established. The feature response model between alpha angle, referring to the dominant scattering mechanism of the target, and crop maturity is illustrated in Fig. 1.

3.3. Effective GDD calculation

We first calculate the daily GDD in the testing area on all the dates. GDD is calculated as:

$$GDD = max(T_{mean} - T_{base}, 0) \quad (2)$$

where T_{mean} stands for the daily mean temperature, and T_{base} represents the base temperature for certain crops. Different crops have different base temperatures, and typical base temperatures are 0°C, 5°C and 10°C for spring crops.

The BBCH to GDD mappings were created at base temperature of 0°C for wheat, 5°C for canola, and 10°C for soybeans and corn. Therefore, in this study, GDDs with all three base temperatures were calculated. Crop seasonings are still different across regions, since the accumulated heat units are also related to the length of daylight in addition to temperature. The accumulated effective GDD (EGDD) model [11] used by AAFC with a day length factor (DLF) according to latitude (L) was calculated to be the variable to better estimate the crop types. The accumulated EGDD was calculated as:

$$EGDD = DLF * \sum GDD \tag{3}$$

$$DLF = \begin{cases} 1 & L = 49^{\circ}N \\ -19.3257 + 1.158643L - & \\ 0.002107689L^2 + 0.0001413685L^3 & 49^{\circ}N < L < 61^{\circ}N \\ 1.18 & L = 61^{\circ}N \end{cases} \tag{4}$$

3.4. Crop classification

Probabilistic procedures for classification use measurement and process models, and dynamic filtering procedure to classify objects that evolve over time. Particle filter, a dynamic filtering procedure for nonlinear and non-Gaussian process or measurement models, has demonstrated effectiveness in canola growth stage estimation in previous studies [7, 12]. As the procedure is based on sensor feature response models at different maturity levels, it does not require observations at any particular frequency, and is not affected by missing measurements. An illustration of the process is shown in Fig. 2. A particle filter dynamically estimates the state of a new observation without restriction to one sensor-specific model, combining estimations from different sensors seamlessly. In this study we only used the RS2 data and this method can be easily extended to include more sensors.

When a new observation enters the model, a probability will be given on the likelihood of crop type. As more dates of data available, the estimation would be more accurate. Since the crops are likely to be planted at different time, different weights will be given on the probability estimations to determine the crop type assignment. Bigger weights were given towards wheat before mid of June, and we did not distinguish corn and soybean before July. Once the probability of one field belonging to one of the classes reaches over 99.9%, the class label will be assigned, otherwise class is determined by the highest probability.

The fields in the three SAs with growth stage observations were used to develop the models, and all the fields with RS2 coverage in 2017 in SA1 were used to test the model. The EGDD calculated from the observation dates and the field-level features from RS2 were calculated per ACI map and fed to the classifier, and the weighted accumulated probabilities determined the crop types. In this study, we just distinguish the four major crop types and ignored the others.

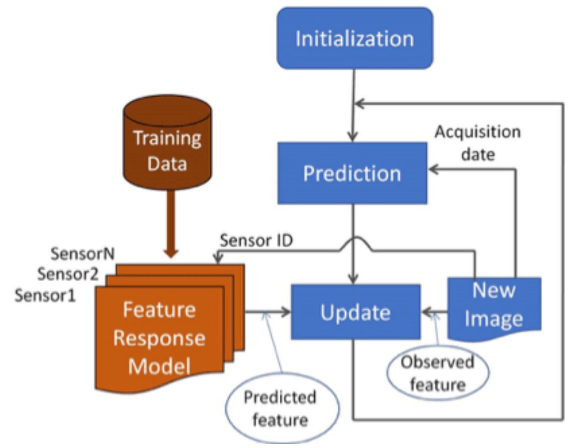


Fig. 2. Illustration of dynamic classification procedure

In comparison, a multi-layer perceptron (MLP) neural network was trained with all features and estimates crop types on single observations. Then the probabilities were accumulated using the same method.

4. RESULTS AND DISCUSSIONS

A total of 415 fields on 14 dates in 2017 in SA1 were tested. F1-score was used to evaluate per crop type accuracy and overall accuracy (OA) for the classifier. The results are shown in Table 2, with comparison with the MLP classifier. The results have shown that our algorithm achieved over 93% accuracy before end of June in classifying canola, wheat and corn/soybean. Since end of June is still relatively early to differentiate corn and soybean in RS2 response, the two classes were combined. According to [6], sensors with shorter wavelength such as TSX, could contribute to better classification of these two crops. The feature response models for TSX is currently in development and will be included in the future. By end of July, 91% overall accuracy was achieved for the four crop types, especially canola with 100% accuracy. Imagery after July mostly contributed to the classification between corn and soybean, and full season classification reached over 96%. Compared with the MLP network, our proposed method performed better in almost all categories. The classification maps are shown in Fig. 3.

In conclusion, our proposed method is able to classify canola, corn, soybean and wheat these four major crops in the Canadian Prairies successfully by the end of July. Earlier classification of corn and soybean may need data from other sensors. We are currently working on the feature models using TSX imagery and will be included in the system. Crop vigour, orientation and soil moisture could be significant sources of error, and our method will be further tested and developed for new data and new regions.

Table 2. Classification Results

Method	Time	Canola	Corn	Soybean	Wheat	OA
MLP	End of June	93.00%	90.60%		83.30%	89.40%
Ours	End of June	**99.00%**	**95.00%**		**85.00%**	**93.40%**
MLP	End of July	100.00%	80.80%	86.50%	99.40%	90.10%
Ours	End of July	**100.00%**	**84.00%**	**83.00%**	**98.00%**	**91.00%**
MLP	End of season	100.00%	82.30%	84.70%	98.70%	93.50%
Ours	End of season	**100.00%**	**95.10%**	**95.70%**	**98.20%**	**96.90%**

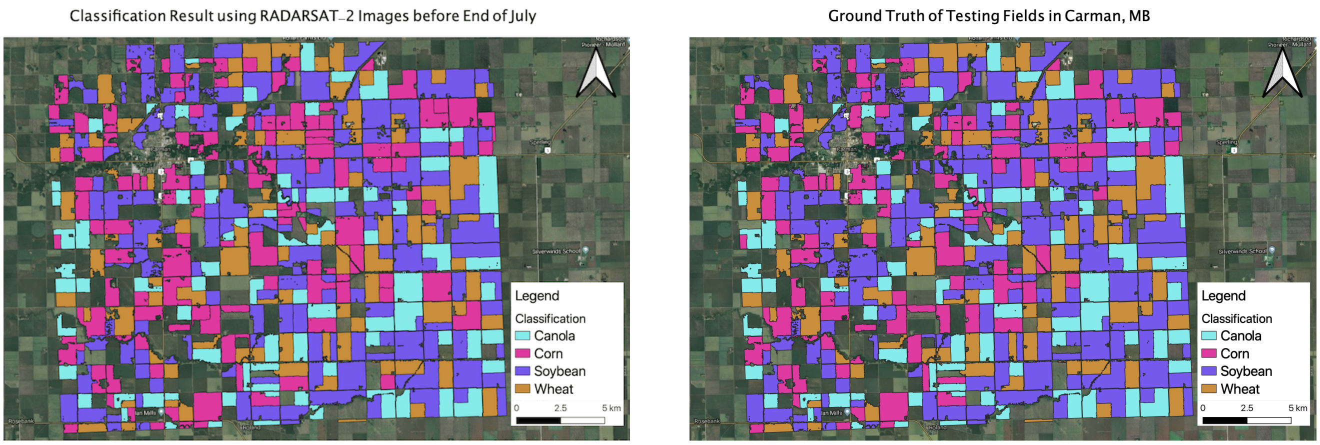


Fig. 3. Classification results before end of July compared with ground truth in Carman, MB

5. ACKNOWLEDGEMENT

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