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Crop Yield Outlooks under Extreme Weather: Lessons Learnt from Canada

Aston Chipanshi, Yinsuo Zhang, Dongzhi, Qi and Nathaniel Newlands

Science and Technology Branch (STB), Agriculture and Agri-Food Canada (AAFC)

1. Introduction

Due to location of the country (middle to polar latitude), Canadian agriculture is at the mercy of extreme climatic events. Heat units are usually insufficient to support the growing of long season crops. Precipitation is equally insufficient because the most productive agricultural soils (chernozems) are found on the Canadian Prairies where annual total precipitation is less than 400mm (Phillips 1990). It is also noteworthy that over 80% of the farmed land and range land are found on the Canadian Prairies (Statistics Canada 2012a, Fig. 1). In spite of the unfavourable weather conditions, Canada's agriculture has adapted over the years to the point where it is one of the major food exporting countries of the world. In order to inform policy and markets on the crop yield prospects, early warning tools such as crop yield models are needed. Traditionally, crop yield outlooks are made using field surveys or questionnaires from sampled farmers (*e.g.*USDA 1999; Statistics Canada 2012b). These methods are resource intensive and reliable estimates are not normally available until long after the growing season. Recent studies (*e.g.* Qian *et al.* 2009; Mkhabela *et al.* 2011; Bornn and Zidek 2012) have shown that crop yield is predictable from agro-climatic indices and remote sensing derived Normalized Difference Vegetation Indices (NDVI) at certain periods of the growing season. Because of the wide availability of both agroclimatic and NDVI data, a crop yield forecasting method was developed within Agriculture and Agri-Food Canada to provide yield outlooks at lead times of 2 to 3 months for major oil and grain crops across Canada. In this study, our goal was to compare crop yield outlooks under extreme weather. We recognized that Canada spends significant amounts of money in compensation to producers because of yield losses due to extreme weather events. For example, it is documented that between 2008 and 2012, federal-provincial disaster relief payouts for climate-related extreme events totaled more than $785 million. Additionally, more than $16.7 billion in crop insurance was paid out during the same period (Public Safety Canada 2015). An accurate outlook is therefore beneficial for planning and designing assistance programs as well as informing commodity brokers and international markets. We therefore tested the performance of the Integrated Canadian Crop Yield Forecaster (ICCYF) (Newlands *et al.* 2014) for a range of weather condition (dry to wet) in order to establish its usefulness as a planning tool.

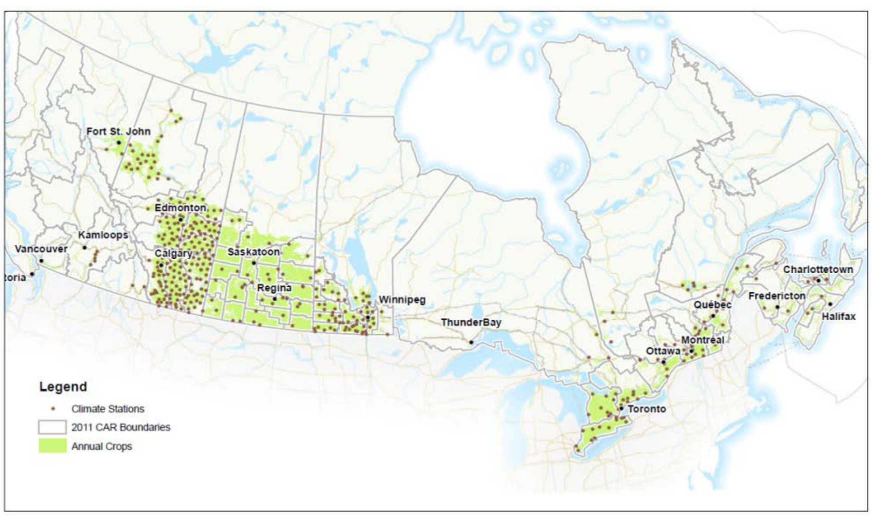

Fig. 1 Study area showing extent of agricultural land, distribution of climate stations and crop modelling units (CARs-Census Agricultural Regions).

2. Methods

The ICCYF yield forecast model was built using historical yield data published by Statistics Canada at the Census

Correspondence to: Aston Chipanshi, Science and Technology Branch, Agriculture and Agri-Food Canada, 300-2010-12th Ave., Regina, SK, S4P 0M3; E-mail: Aston.Chipanshi@agr.gc.ca

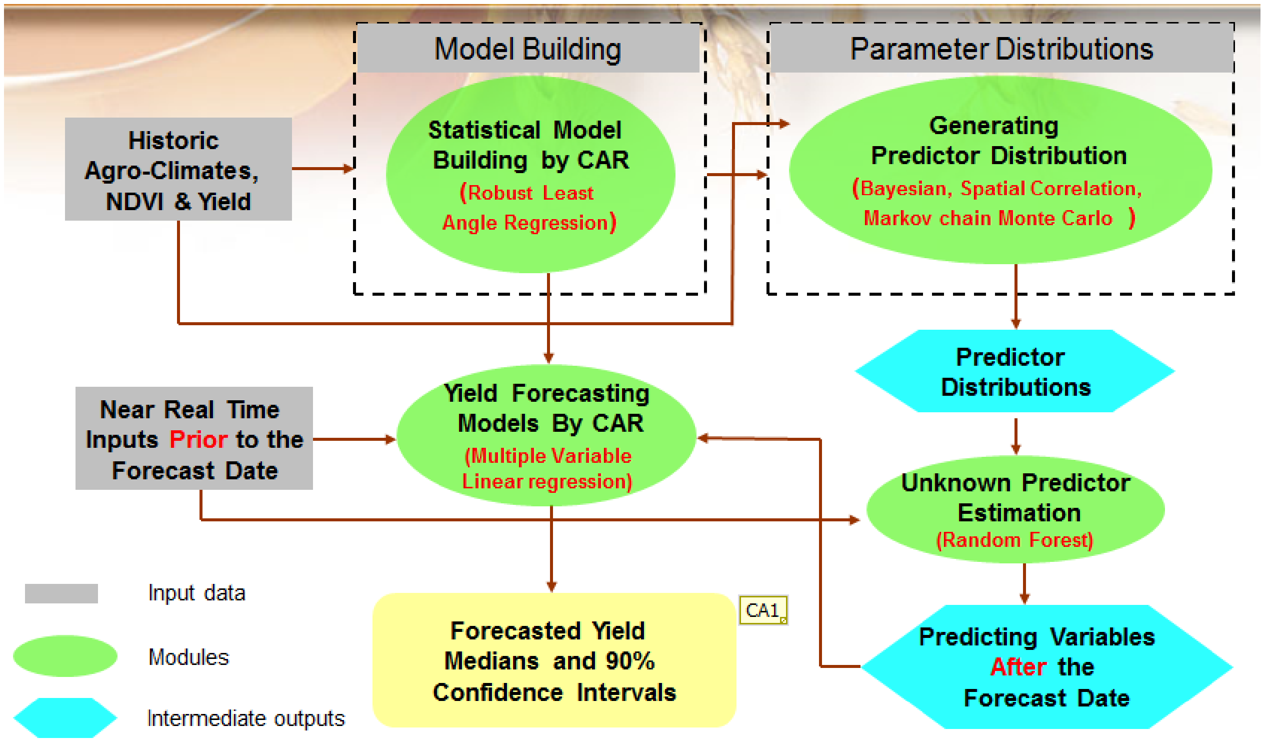

Fig. 2 Model and data flow of the Canadian Crop Yield Forecaster

Agricultural Region (CAR)[1] and the entire climate and NDVI aggregated at the CAR level. The general data and model flow processes are illustrated in Figure 2.The features of the ICCYF are threefold: (1) the integration of agroclimatic predictors such as water stress, cumulative growing degree days and satellite derived NDVI in a GIS environment (2) automated ranking and selection of best predictors using robust least angle regression and (3) sequential forecasting (Bayesian statistics) via the estimation of prior and posterior distribution of predictors from a Markov Chain Monte Carlo scheme and a random forests- statistical technique to estimate the unobserved variables. A detailed description of the method can be found in Newlands *et al.*, (2014) and Kouadio *et al.*, (2014). The validation of the ICCYF for spring wheat, barley and canola in the Canadian Prairies was reported in Chipanshi *et al.* (2015).

The generalized form of the crop yield forecast models is:

$$Y_t = \alpha_0 + \alpha_1 t + \sum_{i=2}^{n} \alpha_i X_{t,i} + \varepsilon_t \qquad (1)$$

where Y_t is the crop yield of year t, α_0 is the regression intercept, $\alpha_1 t$ represent the technical trend of yield over years, $X_{t,i}$ is the predictor i in year t, i could be any of the potential predictors such as NDVI or agroclimatic indices in any of the considered 3-weeks or months, ε_t is the error term.

Extreme weather was defined in terms of unusual impacts on crop yields. This is approximately equivalent to unusual weather that falls out of the range of the historical distribution. The minimum climate period is normally 30 years but we had CARs which had climate records of less than 30 years. Two precipitation based indices were used to define extreme weather as follows:

1. Extreme dryness: AvgSI_68 >1.5SD (2)
2. Extreme wetness: SumPcpn_58>1.5SD (3)

where AvgSI_68 is the average stress index from June to August and stress is defined as the difference between 1 and the ratio of actual evapotranspiration to potential evapotranspiration (1-AET/PET).

[1]http://www5.statcan.gc.ca/cansim/a26?lang=eng&retrLang=eng&id=0010071&tabMode=dataTable&srchLan=-1&p1=-1&p2=9

SumPcpn_58 is the cumulative precipitation from May to August and SD refers to the Standard Deviation of the derived climate variable. In order to determine whether crop yield simulations were sensitive to extreme weather or not, a comparative analysis was made between observed yields and simulated yield over a 25-year period. Results were summarized as overestimates, underestimated or neutral:

1. Over-estimate: Yp-Ys >= 1.5Y_SD (4)
2. Under-estimate: Yp-Ys<=1.5Y_SD (5)
3. Neutral: 1.5Y_SD<Yp-Ys<1.5Y_SD (6)

where Yp is the predicted yield, Ys is the final survey or observed yield and Y_SD is the standard deviation of the historical yield. The following statistics were used to assess model performance under extreme weather prior and after predictor variables were modified as means of testing the skill in model prediction of crop yield: Bravais and Pearson Coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Model Effectiveness Index (MEI) (after Krause *et al.* 2005; Rahbeh *et al.* 2011 and Szulczewski *et al.* 2012). It was hypothesized that, the CCYF performs poorly under extreme weather.

3. Results

Aggregated crop yield (for spring wheat, barley and canola) from the CARs to the provincial and national scales showed good agreement between model simulations and survey yield values that are compiled at the end of the growing season by statistics Canada (Fig. 3). From Canada's provinces with relatively small land area for agriculture (*e.g.* Prince Edward Island-PE, Nova Scotia-NS, and New Brunswick-NB), survey results showed significant annual variations more than those from provinces with a much bigger agricultural land area such as Alberta-AB and Saskatchewan-SK. It has been shown that survey results from smaller provinces are often projections from long term trends and do not always portray actual surveys (Statistics Canada 2012b). The agreement between model simulation and survey results was strongest at the national level (Fig. 3, last horizontal panel) and this suggested that the CCYF tool in its current form is best suited to providing crop yield outlooks at the regional and national scales.

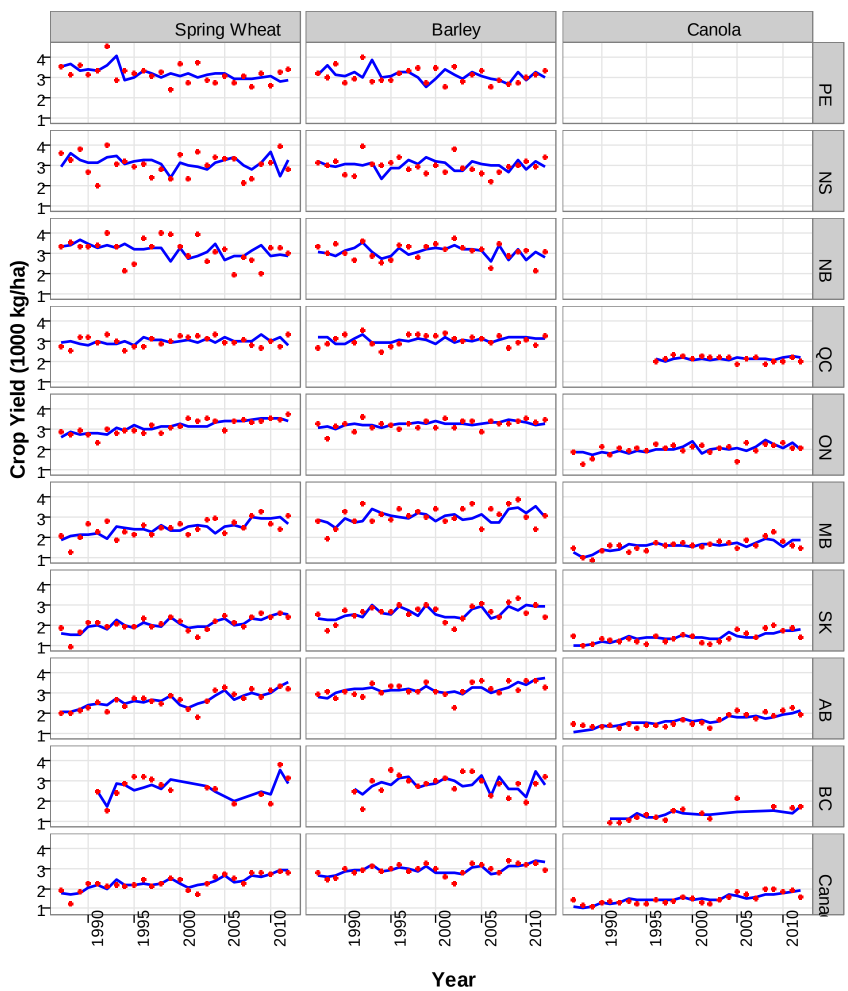

Fig.3 The relationship between simulated and surveyed crop yield at the provincial and national scales blue is model and red is survey

In spite of the good agreement between survey and model simulations, it is evident from Fig. 3 that there were some years e.g. 2001 when model simulation were higher than survey results and there were years when model simulations were lower than survey results (*e.g.* 2005). Therefore, all CARS were binned by extreme weather type as defined in equations 2 and 3. In years with average weather, all the CARs retained simulation results that were not significantly different from survey results for each of spring wheat, barley and canola (Fig. 4). However, when events were dry or wet, simulations came out higher than survey results (over-prediction). For both dry and wet events, under-prediction was the least common in all the three crops studied. Apart from spring wheat, barley and canola, simulations were repeated for soybean and corn for grain. Again, simulated results were higher than survey results under dry weather with under-prediction being less common under both of dry and wet weather conditions.

Recognizing that the ICCYF in its current form overestimates simulated yields in years characterized by extreme dryness, variable selection by Robust Least Angle Regression (RLAR) (Fig. 2) was modified. Instead of the automatic selection of variables, the selection of predictor variables was now based on biophysical considerations. In very dry years for instance, heat stress has implications on final yield of the heat sensitive crops such as canola and if this variable is not selected as a predictor, the final yield could be inflated. When the selection of predictor variables was forced using biophysical considerations, the variance explained in the final yield (R^2) increased, the number of CARs with negative Model Effective Index (negative values of MEI is an indication of no skill in the simulation) dropped and the mean percentage error in modeled values dropped in comparison to the baseline (the baseline result used automatic selection of variables) (Fig. 5). The result in Figure 5 was equally replicated in canola and barley.

4. Summary

Using the Integrated Canadian Crop Yield Forecaster (ICCYF) the simulation of spring wheat, barley and canola compared favourably with observed values at the regional and national scales. In years with extreme dryness, the majority of the CARs over-predicted crop yields. By forcing the model to select predictor variables that have biophysical meaning in relation to the

Yield outlook compared to survey results	Climate Extreme Type (A)			
	Dry	Average	Wet	Total
Neutral	77 (72%)	823 (90%)	70 (86%)	970
Over estimate	26 (24%)	32 (4%)	8 (10%)	66
Under estimate	4 (4%)	53 (6%)	3 (4%)	60
Total	107	908	81	1096

Yield outlook compared to survey results	Climate Extreme Type (B)			
	Dry	Average	Wet	Total
Neutral	106 (72%)	1197 (92%)	88 (79%)	1391
Over estimate	28 (19%)	63 (5%)	24 (21%)	115
Under estimate	13 (9%)	39 (3%)	0	52
Total	147	1299	112	1588

Yield outlook compared to survey results	Climate Extreme Type (C)			
	Dry	Average	Wet	Total
Neutral	85 (79%)	820 (88%)	74 (88%)	979
Over estimate	17 (16%)	51 (5%)	7 (8%)	75
Under estimate	5 (5%)	64 (7%)	3 (4%)	72
Total	107	935	84	1126

Fig. 4 Simulation of crop yield A: Spring wheat, B: Barley and C: Canola under extreme weather.

Index	R2	MEI (neg. / total)	Mean Percent Error	*R2 increased
Baseline	0.39	7/41	17.0	
EGDD_C; SumHeatD; SumPcpn	0.40	5/41	16.6	22/41
CHU; SumHeatD	0.41	5/41	16.7	29/41

Fig. 5 Improvement in spring wheat simulation when predictor variables were selected on biophysical considerations.

development of the crop, the variance between model simulations and observations was reduced. As well, there was a remarkable reduction in the number of CARs that returned no skill when extreme weather conditions characterized the crop calendar. Further improvement in model performance is expected when predictor variable selection is based on crop phenology. This aspect is being investigated.

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