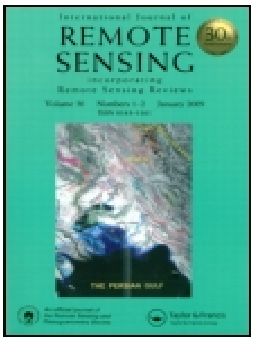

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The early explanatory power of NDVI in crop yield modelling

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The objective of this paper is to study, on a weekly basis, the explanatory power of one satellite-based measurement, the Normalized Difference Vegetation Index (NDVI), for wheat yield modelling in 40 census agricultural regions (CAR) in the Canadian Prairies during the whole growing season using 16 years of NOAA AVHRR satellite data (between 1987 and 2002). We also explore the relative value of NDVI compared with a land-based measurement, the Cumulative Moisture Index (CMI). By developing a series of weekly wheat yield models over the course of the growing season, we are able to determine the accuracy of different models. Our findings indicate that NDVI possesses explanatory power 4 weeks earlier in the season than CMI.

1. Introduction

Severe droughts, increasing competition, and the instability of global grain markets have underscored the importance of obtaining accurate and timely information on crop conditions and potential yield. The benefits include improved inventory, revenue, cost, and risk management along the entire value chain, from producers, to fertilizer, pesticide, and farm chemical manufacturers, to processors, farm associations, cooperatives, and marketing agencies such as the Canadian Wheat Board. Federal, provincial, and state governments, crop insurance companies, and universities also stand to benefit strategically from such advance information.

Two major survey techniques are currently in use for crop yield forecasting and estimation, as described by the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA). The most common is the use of list or multiple frame-based sample surveys of farm operators. Farmers selected for the statistically based sample are asked to report their final harvested yield or their best evaluation of potential yield, based on current conditions. The second is objective yield surveys which utilize plant counts and fruit measurements from random plots in selected fields. Data from multiple years are used to build models that relate pre-harvest counts and measurements to the final post-harvest yield (Allen *et al.* 2002).

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NASS, like Statistics Canada, also uses satellite-based vegetation indices to complement these other forms of crop acreage estimation. Remote sensing data are not *publicly* available early enough in the United States (unlike Canada, as discussed later) to entirely replace early season estimates, but they can still provide important input for improving planted area estimates (not to mention assessing irrigation demand, disease, pest, and weed control, etc.) as the season progresses. Although total crop area does not change much throughout the season, crop conditions change quickly. Timely repeat coverage throughout the season is therefore needed to adequately monitor crop conditions and estimate yields (Allen *et al.* 2002).

Given the predominance of supply issues in the decision-making process of most downstream players in the agricultural commodities industry, any additional production information that can be gleaned from the business environment is likely to be instrumental in strategic sourcing and risk management decisions involving these critical raw materials. Access to near-real-time remotely sensed crop yield data should provide an excellent opportunity to improve upon traditional survey-based decision support tools.

The objective of this paper is to study, on a weekly basis, the explanatory power of one satellite-based measurement, the Normalized Difference Vegetation Index (NDVI), during the whole growing season. Our intent is to identify at what point in the season the greatest gains in explanatory power are made in order to reduce data collection, acquisition, and processing costs accordingly. Therefore, it is not the goal of this study to develop an optimal prediction model, as we will focus mainly on the evolution of estimates of the predictors throughout the growing season. In addition, we explore the relative value of NDVI compared with a land-based measurement, the Cumulative Moisture Index (CMI). This study uses 16 years of data, from 1987 to 2002, from 40 census agricultural regions (CAR) in the Canadian Prairies (figure 1).

2. Previous research

2.1 *Yield forecasting measures*

Over the past 20 years, increasingly sophisticated techniques have been used to predict final annual crop production levels. One such technique is the monitoring of vegetation growth by remote sensing. Various crop vegetation indices exist, but the most commonly cited are the NDVI, the VCI (Vegetation Condition Index), and the TCI (Temperature Condition Index) (Kogan 1990, Unganai and Kogan 1998). Many researchers have related vegetation indices to plant vigor, water stress, leaf area index, yield and production. Tucker *et al.* (1980) were among the first researchers to identify a relationship between NDVI and crop yield using experimental fields and ground-based spectral radiometer measurements. Final grain yields were found to be strongly correlated with the time-integrated NDVI around the time of maximum greenness. Early work relating NDVI to crop yield includes Rasmussen (1992, 1997, 1998), Das *et al.* (1993), Groten (1993), Maselli *et al.* (1993), Quarmby *et al.* (1993), and Smith *et al.* (1995). More recently, numerous studies have reported associations between crop yield and different indices obtained from satellite imagery in various world regions. Examples of such studies are Prasad *et al.* (2006), who used NDVI to predict corn and soybean yields in Iowa, and Labus *et al.* (2002), who predicted wheat yield in Montana. Weissteiner and Kuhbauch (2005) obtained malting barley forecasts from NDVI in Germany. A

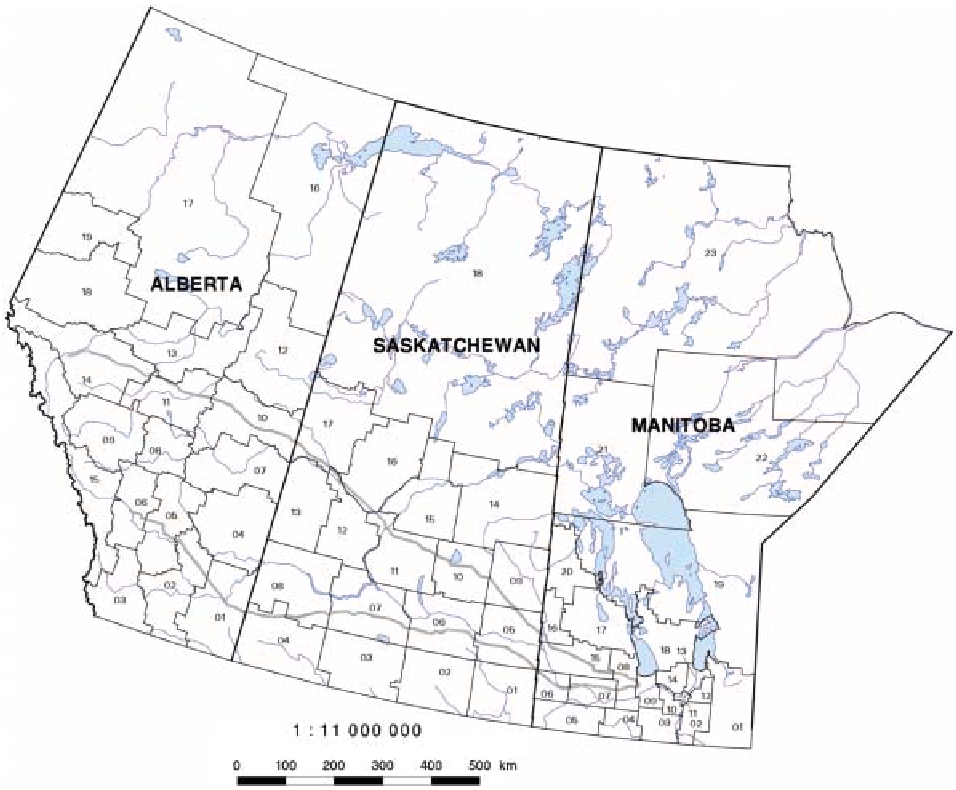

Figure 1. Census agricultural regions (CAR) in the Canadian Prairies (Source: Statistics Canada).

model for maize using NDVI was developed by Mkhabela *et al.* (2005) with data from Swaziland. Under Mediterranean conditions, Royo *et al.* (2003) related NDVI to durum wheat, and Vicente-Serrano *et al.* (2006) predicted wheat and barley yields 4 months before harvest. VCI and TCI were used to estimate corn yield in southern Africa by Unganai and Kogan (1998), in Argentina by Seiler *et al.* (2000) and in China by Kogan *et al.* (2005). VCI was used by Kogan *et al.* (2003) to assess wheat productivity in Kazakhstan, while Domenikiotis *et al.* (2004) used it to estimate cotton yield in Greece. TCI-based estimations of soybean yield were obtained in Brazil by Liu and Kogan (2002). In Mexico, Báez-González *et al.* (2002) assessed corn yield with the NDVI. Finally, Koller and Upadhyaya (2005) related tomato yield to NDVI.

NASS, for example, uses a biweekly composite of the NDVI from the Advanced Very High Resolution Radiometer (AVHRR) on polar-orbiting weather satellites operated by the National Oceanic and Atmospheric Administration (NOAA) for crop-condition monitoring. The EROS Data Center of the US Geological Survey archives the AVHRR data and creates a biweekly composite of the NDVI. NASS procures the biweekly composites, compares the images over time, and links them to the Weekly Crop and Weather Report issued by NASS and the Joint Agricultural Weather Facility (JAWF) of USDA and NOAA (Allen *et al.* 2002). Imagery from the NOAA AVHRR sensor is especially well suited for crop monitoring because of its ideal temporal resolution (daily revisit), appropriate spatial resolution (1.09 km by 1.09 km), wide swath (2700 km), and relative affordability (Nivens *et al.* 2000). Although finer spatial resolution (up to 10 m in the case of Landsat, IRS, and SPOT, and 1 m in the case of Ikonos) is available, such data are much more expensive and have an inappropriate temporal resolution (Ferencz *et al.* 2004). Obtaining more relevant measures through image masking plays an important role in improving crop yield forecasting ability. Kastens *et al.* (2005) compare cropland masking and a new method, yield correlation masking, for crop yield forecasting. In their study, the two methods produce forecasts of comparable accuracy, but the advantage of yield correlation forecasting is that, unlike cropland masking, no land cover map is required.

To date, the most accurate yield estimates from remotely sensed data have been reported in research that used models developed using regression analysis techniques and extensive multitemporal data sets (Das *et al.* 1993, Wang *et al.* 2001, Manjunath and Potdar 2002).

The most important determinants of crop yield over the course of the current growing season are climatic factors. Among such climatic factors, precipitation and temperature exert the strongest influence on both temporal and spatial NDVI patterns and, by inference, on productivity patterns. Wang *et al.* (2001), for example, examined *spatial* NDVI response to precipitation and temperature during a 9-year period in Kansas and found that total deviation from average precipitation explained most of the year-to-year variation in spatial patterns of NDVI. NDVI and precipitation covaried in the same direction (positive or negative) for 60–95% of the total land area.

In unirrigated areas, rainfall is the main factor limiting crop growth and production. Consequently, rainfall distribution parameters in space and time are often incorporated into crop yield models with vegetation indices deduced from remote sensing because such hybrid models show a higher correlation and predictive capability than simple models (Potdar *et al.* 1999, Manjunath and Potdar 2002). In Rajasthan state in India, for example, Manjunath and Potdar (2002) found that the incorporation of monthly rainfall into their regression yield models, in addition to NDVI, improved performance significantly. Their hybrid wheat yield model, using both spectral and rainfall data, was best suited to eastern Rajasthan, where a considerable area was grown under both rain-fed and irrigated conditions.

2.2 *Canadian context*

The Canadian Prairies extend from 49° N (Canada–US border) to 54° N, and from eastern Manitoba to western Alberta (Boken and Shaykewich 2002). The prairie climate is classified as semi-arid or dry-continental with average precipitation of 300–500 mm. Minimum annual precipitation is 280 mm in the southern region along the Alberta–Saskatchewan border. Precipitation increases to the east, north, and west to an average of 560 mm in eastern Manitoba, 410 mm on the northern fringe, and 640 mm along the foothills of the Rockies (PFRA 2001). Subzero temperatures make winter crop growth impossible but short, warm summers are conducive to growing a wide variety of crops. Mean temperatures for the warmest month are 16.1°C in Edmonton and 19.7°C in Winnipeg (Anonymous 2004).

Cereal grain production in Canada is regionalized. The provinces of Alberta, Saskatchewan, and Manitoba produce most of Canada's red spring wheat, durum wheat, barley, oats, and rye. Corn is grown mainly in Ontario and Quebec. From year to year, Canadian producers shift their crops between a wide range of cereal grains, oilseeds and special crops. Factors guiding such decisions are crop rotation, relative market prices, carry-in stocks, and export and domestic demand. According to Agriculture and Agri-Food Canada (AAFC 1999), *wheat* is the most important economic crop in Canada, with production concentrated in the Prairie Provinces and Ontario. In 1998, wheat harvest and production were 11.4 million hectares and just over 24 million tonnes, respectively.

One of the first attempts to construct formal commodity forecasting models for Canadian agriculture was coordinated by Hassan and Huff (1978), based on preliminary models developed by the University of Guelph and Agriculture Canada. These models were developed not only to improve the accuracy and timeliness of existing forecasting techniques, but also to simulate and analyse the impact of various economic policies on a given commodity. Subsequently, there have been several attempts to develop yield models specifically for Canadian wheat. A *monthly* wheat yield model proposed by Walker (1989) is still used by the Canadian Wheat Board (CWB) today, while a *daily* model recently proposed by Boken and Shaykewich (2002) merits consideration. They propose a wheat yield model using daily temperature and precipitation data combined in a cumulative moisture index (CMI), both alone (*daily* model) and with NDVI data (*hybrid* model), for five CARs. Both models improve upon the *monthly* model developed by Walker (1989). Other studies have focused on other crops and have investigated the optimal time to acquire remote sensing information. Ma *et al.* (2001) showed a progressive improvement in the relationship between NDVI and soybean yield over three sampling dates during the growing season. Basnyat *et al.* (2004), in a study in the Canadian prairies, have considered three sampling dates and three crops: pea, canola, and spring wheat. They concluded that there is no single moment that consistently had the highest correlation between NDVI and crop yield for all the crops considered.

The Crop Condition Assessment Program (CCAP) is the only known published example of a specifically Canadian example of a crop-production decision-support tool. The CCAP was initiated in 1987 as a joint project between the Canada Centre for Remote Sensing, Statistics Canada, the CWB, and the Manitoba Remote Sensing Centre (MRSC) to supplement existing farm yield surveys (Reichert *et al.* 1998). Data are collected daily during the growing season at the satellite receiving centre in Prince Albert, Saskatchewan, and transferred to the MRSC for processing. An NDVI map is then produced by Statistics Canada. Because daily NDVI values are reduced by clouds and atmospheric haze, weekly, 7-day, cloud-free composites are constructed (Robertson *et al.* 1992). One can view Statistics Canada's weekly value-added products (free of charge since 2004) in tabular or graphic form, at either the CAR or Census Consolidated Subdivision (CCS) level, through a GIS-enabled website in near real-time throughout the April to October crop-growing season (Reichert and Caissy 2002).

3. Model development

3.1 *Period of study and dependent variable: Canadian annual wheat yield 1987–2002*

The study period is 1987–2002, since NDVI data were available only for those years. The wheat yield variable used was obtained from Statistics Canada. Instead of selecting a specific strain of wheat (Spring Wheat is the most common), we chose to use the yield values for total wheat (the sum of all strains) provided for each CAR.

3.2 *Independent variables: NDVI and CMI*

The first variable, NDVI, is based on average weekly NDVI data obtained from the CCAP for crop and pasture/rangeland masks (Reichert and Caissy 2002). Numerous variations in NDVI-based independent variables have been developed in crop yield modelling over the years. As yield is influenced most by crop conditions during the *heading* or peak phase of growth, for example, Boken and Shaykewich (2002) used average NDVI during July and standard deviation in NDVI data during July (among other variables) in their work. Labus *et al.* (2002), on the other hand, used the summation of NDVI growth profiles through each consecutive month of the growing season and the summation of NDVI over selected critical dates (e.g. in July), with similar success.

The final choice of a cumulative NDVI variable was therefore an attempt to blend the characteristics of variables that had achieved the best results in previous studies, but with a distinct focus on practicality of use rather than pure theoretical value. Since the ultimate aim of our model is to model yield and production levels as early as possible in the growing season, variables derived from data spanning the entire season were therefore immediately eliminated. Estimates obtained at or around harvest time add little value to the traditional decision support systems and reporting mechanisms already described.

For this reason, and based on the factors discussed above, we decided to use the cumulative average weekly NDVI, or in other words, the sum of weekly average NDVI values to date, as the main NDVI-based independent variable in all yield models. This single variable allows one to capture the cumulative effect of both climatic conditions and farming practices (e.g. irrigation, fertilizer, etc.) up to and including the current week of evaluation.

CMI is the *daily moisture index* (DMI) cumulated over the growing period—from seeding to harvest—reflecting the extent to which a crop's daily moisture requirement has been met.

Although admittedly somewhat oversimplified, CMI is basically an index which incorporates the daily heat useful to a crop through *accumulated growing degree days* (AGDD). It begins with an estimation of cumulative soil moisture (*csm*) on the first day of the growing season (based on weighted average precipitation during the previous 12 months) and subsequently involves a crop-water requirement (*cwr*) calculation and a soil water budgeting (*swb*) procedure based on such factors as daily temperature, precipitation, crop phenology, evapotranspiration characteristics of the soil, and so on. More details on the calculation of CMI can be found in Boken and Shaykewich (2002).

Several authors have confirmed the importance of the *cumulative* effect of moisture on plant growth by summing precipitation on a weekly or biweekly basis for the current season and part (or all) of the previous season (Wang *et al.* 2001, Boken and Shaykewich 2002, Manjunath and Potdar 2002). In a study of the *temporal* response of NDVI to temperature and precipitation, for example, Wang *et al.* (2003) found that total precipitation during a 15-month period was most strongly correlated with average seasonal NDVI. Based largely on the work of Boken and Shaykewich (2002), an average CMI value was calculated for each CAR on a weekly basis throughout the growing season using data recorded at some 130 weather stations across the Prairies.

3.3 *Control variables: Soil type and percentage of wheat*

Soil type was chosen as a control variable, based on the predominant soil type of the cropland in each CAR, as described by Statistics Canada. Interestingly, this independent variable was not included in any of the formal models reviewed in the literature but is occasionally used by some authors to explain certain particularities of their findings (Reichert *et al.* 1998, Boken and Shaykewich 2002, Manjunath and Potdar 2002). It was expected that the inclusion of this nominal variable—subarid, semi-arid, and subhumid—would improve the model's performance.

The second control variable used in our model was the proportion of wheat to total cropland for each CAR. This proportion was expressed in terms of harvested acres of wheat as a percentage of total harvested acres (PERWHEAT), calculated annually. Admittedly, the use of *seeded* acres (versus *harvested* acres) would have been preferable; to account for losses and spoilage throughout the growing season, but unfortunately, such data were not available for all years. Like soil type, to the best of our knowledge, this variable has never been formally included in previously published yield models, most probably because the majority of yield models have been limited to only one (dominant) crop. In Canada, for example, Boken and Shaykewich (2002) limited their study to five CARs in Saskatchewan where wheat represented 60% of total grain production.

3.4 *Statistical model*

As mentioned above, most previous crop yield models have been based on linear regression equations. This kind of approach, however, often fails to consider a possible geographic dispersion correlation effect. For example, if two CARs share a boundary, they will likely experience more similar climatic conditions (and, thus, exhibit more similar yield patterns) than two CARs that are separated by a greater distance. Distances were therefore calculated between the geographical centres of each CAR, using latitude and longitude, in order to exploit spatial patterns of variation in yield in adjacent (or nonadjacent) CARs. Linear mixed effects models with random CAR effects and a spatial power covariance structure were fitted (Fitzmaurice 2004). The random CAR effects account for local variations (at the CAR level) due to differences in farming practices (irrigation, crop rotation, etc.) that are not explained by other explanatory variables. Modelling the spatial correlation provides more accurate estimates of the standard error of the parameters and thus more valid statistical inferences.

Three wheat yield models were developed. All models include the two control variables (soil type and percentage of wheat). Model A adds only CMI, model B adds only NDVI and model C uses both.

A different model ($k=1 \ldots 18$) was developed for each of the last 18 weeks of the growing season. All three models were adjusted on a weekly basis, leading to 54 models (18 weeks $\times$ 3 models). Each of these 54 models was adjusted using 640 observations (40 CARs $\times$ 16 years from 1987 to 2002). Only data for the last 18 weeks of a typical 20-week growing season (May–August) were used to adjust the models because of missing NDVI data. This omission was deemed acceptable because the accuracy of very early crop yield estimates is typically quite low. The first week in May was assigned as the third week of the growing season for each year. It should be noted that the value of soil type is constant throughout the 16 years while the value of PERWHEAT varies only on a yearly basis. As for NDVI and CMI, they evolve on a weekly basis.

An example using model C illustrates more clearly how these covariates fit:

$$\text{Yield}_{ij} = \alpha_i^{(k)} + \beta_1^{(k)}\text{SOILTYPE}_i + \beta_2^{(k)}\text{PERWHEAT}_{ij} + \beta_3^{(k)}\text{CMI}_{ij}^{(k)} + \beta_4^{(k)}\text{NDVI}_{ij}^{(k)} + \varepsilon_{ij}^{(k)},$$

where the indices and variables are defined as follows: i=1, …, 40 CAR; j=1, …, 16 years of the study period (1987–2002); k=1, …, 18 (last) weeks of each growing season (May to August)—one model for each week; $\alpha_i^{(k)}$ = the random effect, with variance σ_α^2, for CAR i for the kth model (week); YIELD$_{ij}$=the final annual yield (kg ha^{-1}) for CAR i in year j; SOILTYPE$_i$=one of three dominant soil types for CAR i modelled with dummy variables (constant over the entire period); PERWHEAT$_{ij}$=proportion of wheat as a percentage of total harvested acres for CAR i in year j (constant over the season); $CMI_{ij}^{(k)}$ = the cumulative moisture index value for CAR i in year j for the kth model (week); NDVI$_{ij}^{(k)}$ = the cumulative average weekly NDVI value for CAR i in year j for the kth model (week); $\varepsilon_{ij}^{(k)}$ = individual error term for CAR i in year j for the kth model (week), which models the spatial correlation with a term of the type $\sigma^2\rho^{d_{st}}$ where d_{st} is the distance between CAR s and t.

In other words, the model allows us to exploit the fact that the closer one CAR is to another, the more likely it is that their yields will be correlated. Conversely, this correlation tends to decrease exponentially as a function of the distance between CARs. Indeed, for a given week, the correlation between the yields in CAR s and CAR t is given by $\left(\sigma_\alpha^2 + \sigma^2\rho^{d_{st}}\right)\left(\sigma_\alpha^2 + \sigma^2\right)^{-1}$, which in turn may be different for each week. A temporal correlation was also a possibility, and in fact was expected, but proved to be insignificant.

Models A and B are defined similarly to model C, but include only CMI or NDVI, respectively. The models were adjusted using PROC MIXED in SAS (SAS Institute Inc; www.sas.com), which is a general procedure to fit linear mixed models allowing many different correlation structures (Littell *et al.* 1996).

3.5 *Model performance measurement criteria*

Several measures were chosen to evaluate the models. The first is the Bayesian Information Criterion (BIC), also called Schwarz's Bayesian Criterion (Schwarz 1978). By penalizing the addition of parameters, this likelihood-based criterion allows the comparison of models with different numbers of parameters (like the adjusted R^2 in ordinary regression). With the version reported in this paper, smaller BIC values indicate better models.

Although measures such as R^2 are not usually used with random effect models, they were computed using the usual formulas (using the model containing only an intercept as the baseline) to allow comparisons with previous work.

It was also deemed important to measure the contribution of the various independent variables over the course of the growing season by examining the significance (p-values) of the individual beta of the independent variables for each model throughout the growing season.

4. Results and discussion

It should be noted that all the models contain both control variables (soil type and percentage wheat), and their influence on the models will not be further discussed. Moreover, the parameter modelling the spatial correlation is significant in all models. However, complete and detailed results are available upon request from the second author.

Figures 2 and 3 show the values of the estimates of CMI and NDVI in the models in which they are involved. We see that NDVI becomes significant at week 7 in both models B and C (figure 2). As for CMI, it becomes a significant variable by week 11 in model A and 1 week later in model C, in which NDVI is also included (figure 3). Yet, in model C, the parameter estimate of CMI is considerably smaller than in model A. The same is also true of NDVI, but to a far lesser extent. This indicates that part of the explanatory power of CMI in model A is already included in the variance explained by NDVI.

Figure 4 presents the BIC values for each model throughout the growing season. As expected, for each model, the closer we get to the harvest period, the smaller the BIC is, indicating that the model is better. The curves decrease in an 'S' pattern. This indicates that there is a period, roughly between weeks 5 and 15, during which the model's performance clearly improves until it stabilizes.

The points at which the variables NDVI and CMI become significant for the first time in the models in which they are involved are indicated in figure 4. As we can see

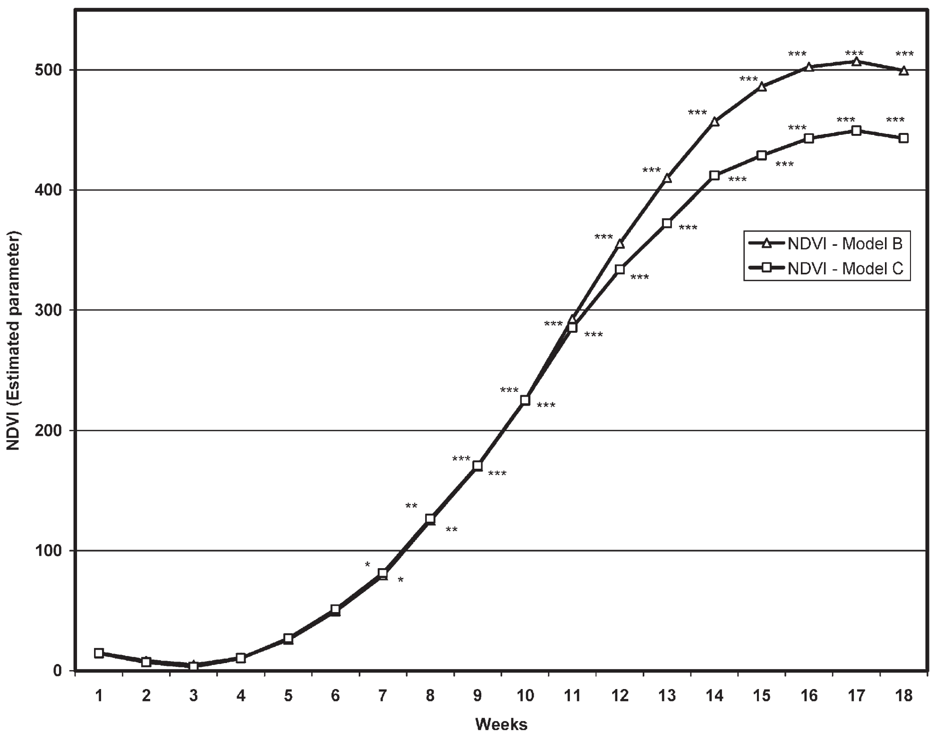

Figure 2. Evolution of the estimated parameter of NDVI throughout the growing season. $^*p<.05$; $^{**}p<.01$; $^{***}p<.001$.

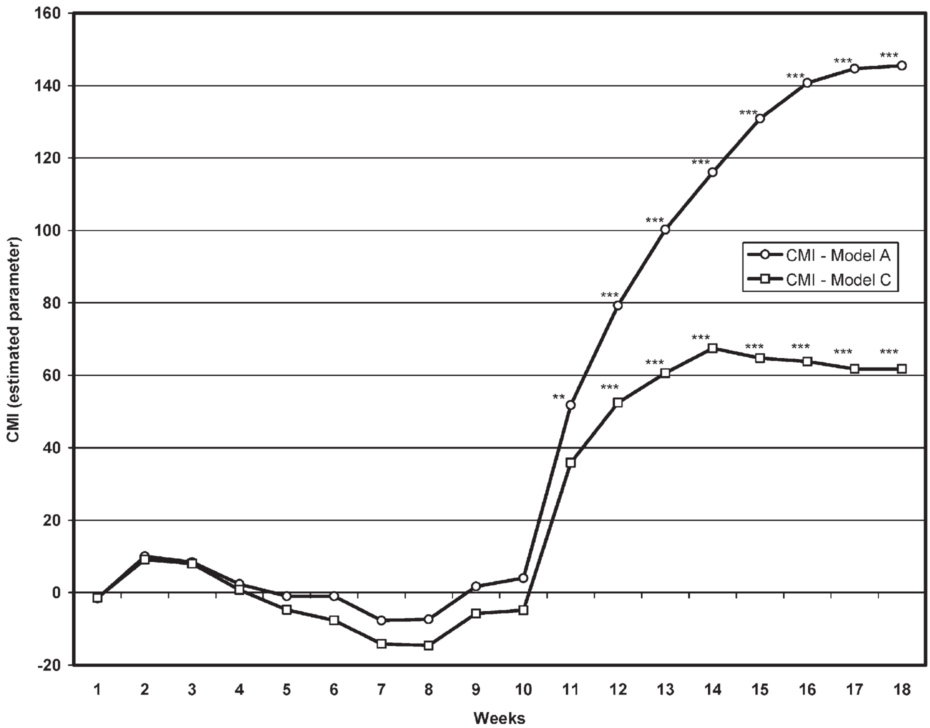

Figure 3. Evolution of the estimated parameter of CMI throughout the growing season. *$p<.05$; **$p<.01$; ***$p<.001$.

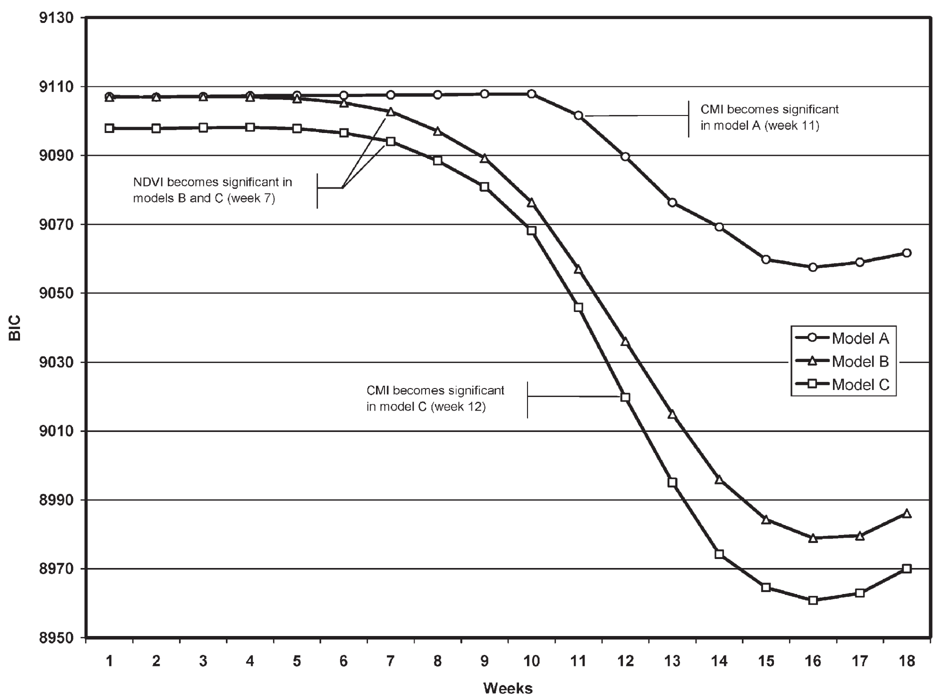

Figure 4. Evolution of BIC throughout the growing season.

in figures 2 and 3, NDVI becomes significant 4 weeks before CMI becomes significant in any of the models.

The models are also comparable across weeks. Thus, according to the BIC, the model that includes only NDVI is better than that which includes only CMI in each week. Moreover, the BIC value of model B at week 11 is smaller than that of model A in any given week during the whole season.

All these elements indicate that, should we have to choose between models A and B, we would prefer model B. But if both variables are available, using them together produces an even better model according to the BIC criterion.

As mentioned earlier, R^2 is not usually used with random effects models. But since it is a well-understood measure, we provide it in figure 5. We can observe that the R^2 of the model that includes only NDVI increases earlier than that of the model including only CMI. Nevertheless, the best performance is achieved by model C (using both variables), which achieves more than 55% of variance explained at the end of the season (week 18).

Bearing in mind that it is difficult to compare R^2 values for studies conducted in different contexts and different countries, we present a brief discussion about previous studies on wheat yield using NDVI. In Canada, Boken and Shaykewich (2002) obtained an average R^2 value of 0.78, but their results were based on daily (versus weekly) models, and they included only five CARs with optimal variability in drought occurrence and yield (versus all 40 Prairie CARs in the present study). In other countries, Labus *et al.* (2002) and Manjunath and Potdar (2002) were among the few authors to publish R^2 values. The former reported an average district adjusted R^2 value of 0.71 (across 15 districts) and a regional adjusted R^2 value of

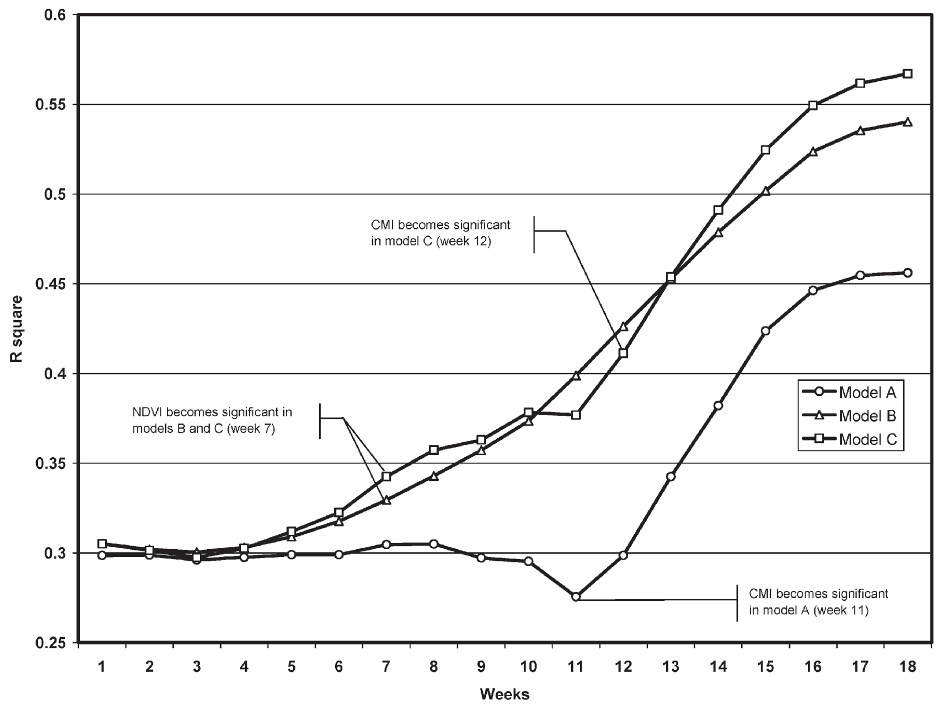

Figure 5. Evolution of R^2 throughout the growing season.

0.41 in Rajasthan, while the latter reported a maximum R^2 value of 0.70 in Montana using variables based on data up to the end of August. More recently, Vicente-Serrano *et al.* (2006) obtained an R^2 value of 0.88 for data from a small arid region, the Monegrillo municipality in the Middle Ebro Valley in Spain.

The R^2 values reported in figure 5 come from singles models (one for each week) that include all 40 CARs. However, there is considerable variability among CARs. For example, looking at CARs individually in week 13, we observe that the minimum R^2 for a single CAR is 0.02 while a maximum of 0.90 is attained for another CAR. The average R^2 value over the 40 CARs in week 13 is 0.45. Consequently, the comparison with other studies is not straightforward and depends on, among other factors, the number of regions considered and also on their sizes.

However, the goal of this study was not to provide an optimal prediction model, but to investigate at what point in time the predictors become significant. Fine tuning and optimizing the prediction model at the CAR level using independent data will be the focus of future work.

5. Conclusion and practical implications

The originality of this study resides in the fact that, through the development of a series of weekly wheat yield models over the course of the growing season, we were able to determine the evolution of the accuracy of the models both as a whole and by individual independent variables. In addition, our models are based on near-real-time satellite-based remotely sensed data; moreover, they are adjusted using all CARs within the Canadian Prairies, not just a subset of regions.

Our findings indicate that using NDVI allows a competitive yield model to be developed much earlier in the season (4 weeks earlier) than a model using a common land-based variable, the CMI. Moreover, the model with NDVI alone is better than the model using CMI alone throughout the season. Should one have to build a yield forecast in a region of the world where land-based measurements are not easily accessible, our results show that we could rely on remote sensing and expect to generate an adequate model. Yet, if both types of measurements are available, an even better model could be constructed.

Although these results may be of theoretical interest to some researchers, they are of practical importance to all industry players that need to obtain upstream business intelligence because they indicate both when the models begin to add the most incremental value to strategic decision support and which types of data are most important over the course of the season. Railway companies, for example, such as Canadian Pacific Railway (CPR), operating mainly in the southern Canadian Prairies, and Canadian National (CN), operating mainly in the north, stand to benefit from using the information on geographically localized production yield earlier in the season. By continuously refining their total carload estimates based on the latest weekly production forecasts, the accuracy of the estimates of associated revenues would increase accordingly, allowing the railway to optimize both daily operations and short-term investment decisions. Another practical application would be for government agencies such as the CWB. Being able to anticipate production yield earlier would enable these agencies to develop hedging strategies to better cover operational risks. An additional application would be for crop insurance organizations. The earlier these organizations can predict yield patterns on a provincial aggregate basis, the sooner (and better) they can predict the expected total number of claims by participating producers.

The main focus of this paper was to study how the explanatory power of NDVI changes as the growing season progresses. One possibility for future research would be to develop, as early in the season as possible, yield-forecasting models that are accurate enough for practical purposes. Another research avenue would be to assess the application of this method for other crops, including crops with long growth cycles (e.g. corn) and shorter growth cycles (e.g. sunflowers).

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