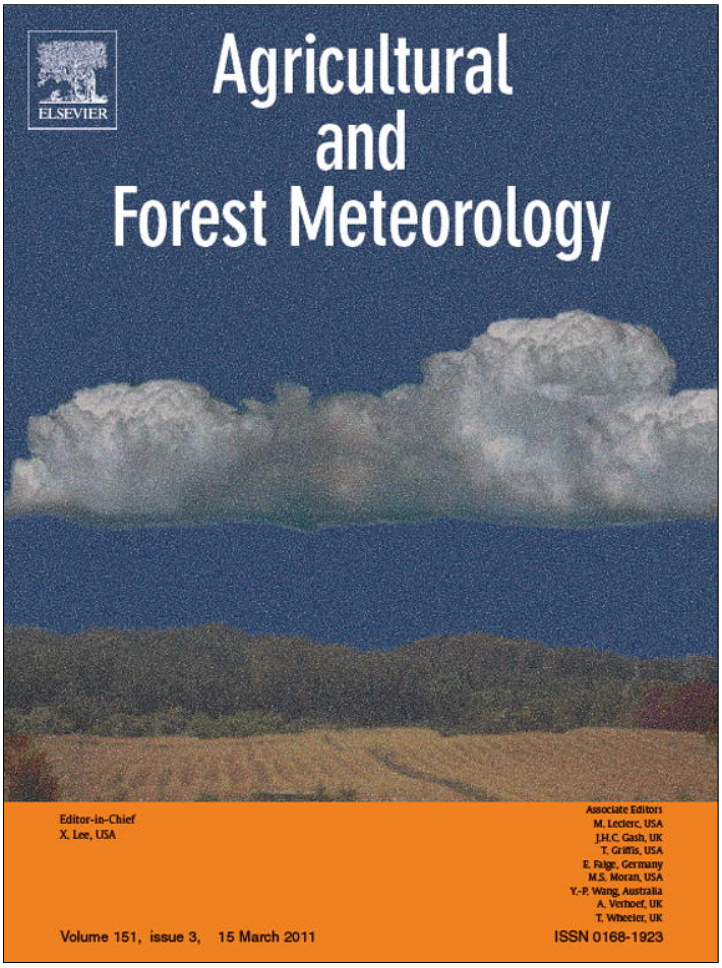
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# Crop yield forecasting on the Canadian Prairies using MODIS NDVI data

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ABSTRACT

Although Normalised Difference Vegetation Index (NDVI) data derived from the advanced very high resolution radiometer (AVHRR) sensor have been extensively used to assess crop condition and yield on the Canadian Prairies and elsewhere, NDVI data derived from the new moderate resolution imaging spectroradiometer (MODIS) sensor have so far not been used for crop yield prediction on the Canadian Prairies. Therefore, the objective of this study was to evaluate the possibility of using MODIS-NDVI to forecast crop yield on the Canadian Prairies and also to identify the best time for making a reliable crop yield forecast. Growing season (May–August) MODIS 10-day composite NDVI data for the years 2000–2006 were obtained from the Canada Centre for Remote Sensing (CCRS). Crop yield data (i.e., barley, canola, field peas and spring wheat) for each Census Agricultural Region (CAR) were obtained from Statistics Canada. Correlation and regression analyses were performed using 10-day composite NDVI and running average NDVI for 2, 3 and 4 dekads with the highest correlation coefficients ($r$) as the independent variables and crop grain yield as the dependent variable. To test the robustness and the ability of the generated regression models to forecast crops grain yield, one year at a time was removed and new regression models were developed, which were then used to predict the grain yield for the missing year. Results showed that MODIS-NDVI data can be used effectively to predict crop yield on the Canadian Prairies. Depending on the agro-climatic zone, the power function models developed for each crop accounted for 48 to 90%, 32 to 82%, 53 to 89% and 47 to 80% of the grain yield variability for barley, canola, field peas and spring wheat, respectively, with the best prediction in the semi-arid zone. Overall (54 out of 84), the % difference of the predicted from the actual grain yield was within ±10%. On the whole, RMSE values ranged from 150 to 654, 108 to 475, 204 to 677 and 104 to 714 kg ha$^{-1}$ for barley, canola, field peas and spring wheat, respectively. When expressed as percentages of actual yield, the RMSE values ranged from 8 to 25% for barley, 10 to 58% for canola, 10 to 38% for field peas and 6 to 34% for spring wheat. The MAE values followed a similar trend but were slightly lower than the RMSE values. For all the crops, the best time for making grain yield predictions was found to be from the third dekad of June through the third dekad of July in the sub-humid zone and from the first dekad of July through the first dekad of August in both the semi-arid and arid zones. This means that accurate crop grain yield forecasts using the developed regression models can be made one to two months before harvest.



## 1. Introduction

Grain crop production plays a vital role in the economy of the Canadian Prairie Provinces (i.e., Alberta, Saskatchewan and Manitoba), with the main grain crops being wheat, canola, barley and field peas. In 2008, the area under these four crops in western Canada was about 21 million ha, of which, 10 million ha were under wheat (Statistics Canada, 2009b). A comparison of annual wheat production (Statistics Canada, 2009a,b) and wheat marketing (Canadian Wheat Board, 2008) in western Canada shows that about 75 to 80% of the wheat grown on the Prairie Provinces is exported. Given the importance of these grain crops to the economy of the Canadian Prairie provinces and Canada as a whole, early crop yield forecasting is fundamental and would go a long way in helping policy makers and grain marketing agencies such as the Canadian Wheat Board (CWB) in planning for exports.

The Normalised Difference Vegetation Index (NDVI) data derived from the Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA) have been used extensively to monitor crop condition and forecast yield and subsequently production in many countries including Canada. For example, Mkhabela and Mkhabela (2000) and Mkhabela et al. (2005) developed regression models using

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AVHHR-NDVI data to forecast cotton and maize yield, respectively, in Swaziland and concluded that the yield of both crops could be accurately predicted at least 2 months before harvest. Unganai and Kogan (1998) reported that the vegetation conditioning index (VCI) derived from AVHHR-NDVI correlated significantly ($r$ = 0.32 to 0.95) with maize yield in Zimbabwe during the critical grain filling stage. Similarly, Lewis et al. (1998), found that AVHHR-NDVI significantly correlated ($r$ = 0.75, $p$ < 0.05) with maize yield in Kenya and reported that maize production forecasts could be made a month before harvest. In Spain, Vicente-Serrano et al. (2006) combined AVHHR-NDVI data and drought indices and were able to predict wheat and barley yield four months before harvest. Their predictive models explained 88% and 82% of the variation in wheat and barley yield, respectively.

On the Canadian Prairies, Bullock (1992), Hochheim and Barber (1998), Boken and Shaykewich (2002) and Wall et al. (2008) showed the usefulness and reliability of AVHHR-NDVI data for forecasting wheat yield before harvest. Bullock (1992) reported that reliable wheat yield estimates could be made by early August, which is timely enough to be useful for the CWB operations and other users. On the other hand, Basnyat et al. (2004) investigated the relationship between AVHHR-NDVI and canola, field peas, spring wheat and durum wheat grain yield and concluded that NDVI data acquired during the period 10 to 30 July were the best for forecasting grain yield of spring-seeded crops on the Canadian Prairie. Similarly, Holzapfel et al. (2009) found that NDVI data acquired between the six-leaf stage and the beginning of flowering using a hand-held optical sensor were highly correlated to canola seed yield ($R^2$ = 0.35; $p$ < 0.001). The authors reported that the correlations improved to $R^2$ = 0.36 to 0.43 when the experimental locations were categorised by soil zones; a further improvement ($R^2$ = 0.53 to 0.67) was realised when the NDVI was divided by growing degree days (GDD) with a base temperature of 5 °C. A comprehensive list of studies that have looked at the relationship between AVHHR-NDVI data and yield for different crops can be found in Funk and Budde (2009).

Recently, studies have been conducted to relate NDVI data derived from the new Moderate Resolution Imaging Spectroradiometer (MODIS) and crop yield (Doraiswamy et al., 2004, 2005; Ren et al. 2008; Funk and Budde, 2009; Becker-Reshef et al., 2010) and also for vegetation drought monitoring (Guo and Richard, 2004; Wan et al., 2004; Gu et al., 2007, 2008). The advantage with MODIS is that it has a better spatial resolution (250 m) and a better radiometric calibration than AVHRR allowing more accurate crop yield forecasts (Doraiswamy et al., 2004, 2005; Schut et al., 2009).

Although several studies have been conducted to establish the relationship between AVHHR-NDVI and crop yield on the Canadian Prairies, no such studies have been conducted to relate MODIS-NDVI data to crop yield. Moreover, most of the studies that have related AVHHR-NDVI to crop yield on the Canadian Prairies concentrated on wheat, probably due to the fact that wheat is the largest crop on the Prairies. The objectives of this study therefore, were to: (i) evaluate the potential of using MODIS-NDVI data to forecast crop (wheat, canola, barley and field peas) yield on the Canadian Prairies and (ii) identify the best time for making a reliable crop yield forecast. The ultimate goal is to design a tool for agricultural drought assessment in western Canada that will include MODIS-NDVI as one of several independent variables to improve the capability to delineate the spatial extent of drought-affected areas.

## 2. Materials and methods

### 2.1. Description of study area

The Canadian Prairies include the provinces of Alberta, Saskatchewan and Manitoba (Fig. 1) and collectively have about 30 million ha of crop land. The Prairies extend northward from 49°N to 54°N latitudes and westward from 96°W to 114°W longitudes (Boken and Shaykewich 2002) and have three distinct agro-climatic zones including sub-humid, semi-arid and arid (Fig. 2). Precipitation ranges from 300 to 500 mm per annum (Environment Canada, 2008) and is often lower than crop evapotranspiration (crop water demand), thus moisture deficit is one of the major constraints to crop production on the Prairies (Nadler, 2007). Average precipitation for the wettest month (June) is 87, 75 and 90 mm at Edmonton, Regina and Winnipeg, respectively. Overall average winter and summer temperatures are −10 °C and 15 °C, respectively. Average temperatures for the warmest month (July) are 15.9 °C at Edmonton, 18.8 °C at Regina and 19.5 °C at Winnipeg (Environment Canada, 2008). Most of the Prairie consists of Brown, Dark Brown and Black and Gray Chernozemic soils (Nadler, 2007; DePauw et al., 2011). The soils are generally associated with the agro-climatic zones, i.e., the Black and Gray soils are dominant in the sub-humid zone, the Dark Brown soils in the semi-arid zone and the Brown soils in the arid zone (Fig. 2). Average annual precipitation in the Black and Gray, Dark Brown, and Brown soil zones range from 373 to 558, 350 to 435 and 334 to 385 mm, respectively (DePauw et al., 2011).

### 2.2. Crop yield data

Statistics Canada collects comprehensive data on the total area planted/harvested, yield and production of all crops across Canada at various resolutions including Census Agriculture Region (CAR) (Fig. 1). Crop yield data by CAR for the period 2000 to 2006 were obtained from Statistics Canada (Statistics Canada, 2007). This time period included a period of widespread, severe drought (2001 to 2002) as well as a period of high crop yield (2005 to 2006) in western Canada (Wheaton et al., 2008). Therefore, the study period provided the opportunity to test the methodology over a wide range of crop yield conditions. Yield data for four crops including barley, canola, field peas and spring wheat from the 40 CARs (8 in Alberta, 20 in Saskatchewan and 12 in Manitoba) were utilised in this study. Over the 10 year period from 1997 to 2006, the four crops evaluated represented an average of 75% of the total harvested area of all annual crops in these three provinces. The yield data were not complete for each CAR, crop (except for barley) and year because of gaps that result from either lack of respondents or data suppression by Statistics Canada to prevent disclosure of any information deemed confidential. In all, there were no missing data for barley, while only 0.7, 4.6 and 6.8% of the data were missing for canola, field peas and wheat, respectively.

The CARs were categorised (allocated) into three agro-climatic zones i.e., sub-humid zone, semi-arid zone and arid zone (Fig. 2). These agro-climatic zones coincide closely with the location of the Great Groups within the Chernozemic soil order on the Prairies, Dark Gray-Black, Dark Brown and Brown, respectively. Long-term climatic conditions, specifically the level by which annual potential evapotranspiration exceeded annual precipitation, has determined native vegetation on the Canadian Prairie, which in turn affected soil organic matter levels and the resulting soil colour (Soil Classification Working Group, 1998). After the categorisation, the sub-humid zone, semi-arid zone and arid zone had 25, 7 and 8 CARs, respectively. Hochheim and Barber (1998) reported that the NDVI correlated better with crop yield when the CARs were stratified using summer-fallow and soil type. Similarly, Holzapfel et al. (2009) observed that categorising experimental locations by soil group and developing regression models for each soil group increased the correlation between NDVI and canola grain yield. Similar results were reported by Ma et al. (2001) when studying the relationship between NDVI and soybean yield in Ontario. As previously mentioned, the soil

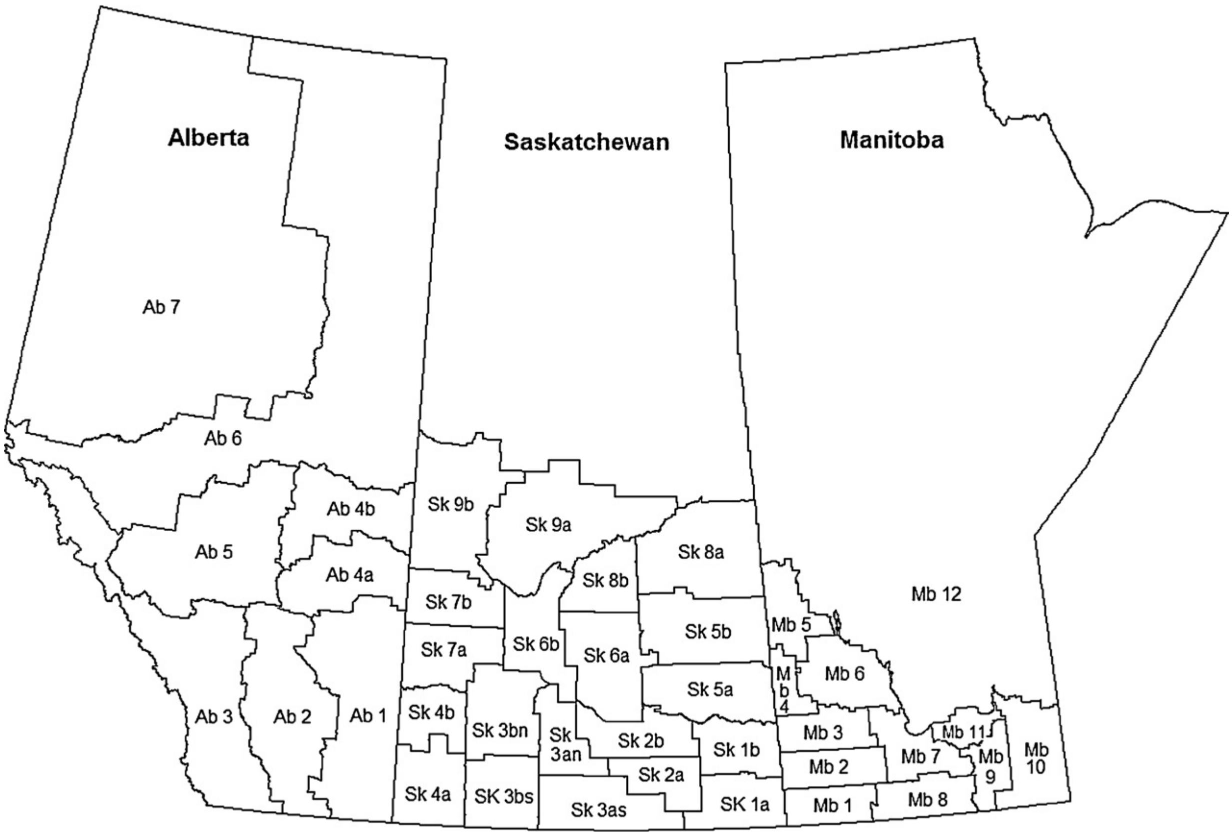


**Fig. 1.** Census agriculture regions (CAR) of the Prairie Provinces.

types on the Canadian Prairies tend to follow the agro-climatic zones.

### 2.3. MODIS-NDVI data processing

Processed growing season (May–August) Moderate Resolution Imaging Sprectroradiometer (MODIS) 10-day composite Normalised Difference Vegetation Index (NDVI) data for the Canadian Prairies for the years 2000 to 2006 were obtained from the Canada Centre for Remote Sensing (CCRS). Data for the third dekad of June 2001 were missing and thus were filled by linear interpolation. The theory of NDVI is based on properties of green vegetation to reflect the incident solar radiation differently in two spectral wavebands: the visible red 0.620 to 0.670 mm wavelength (Band 1) and near-

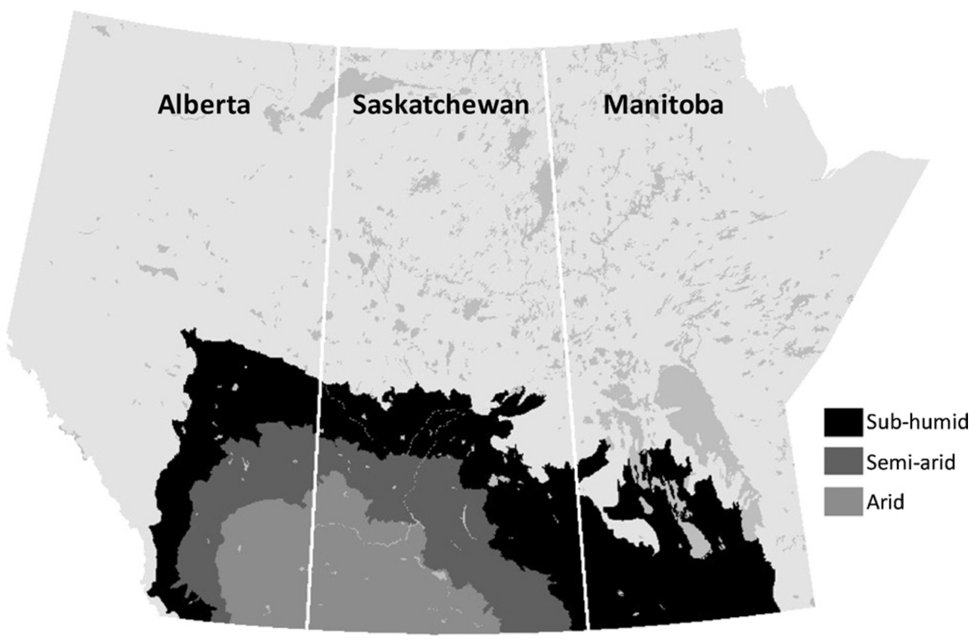


**Fig. 2.** Climatic regions of the Prairie Provinces.

**Table 1**
Best-fit models for each crop in each agro-climatic zone on the Canadian Prairies.

| Crop | Agro-climatic zone | Model | $N$ | $R^2$ | SEM | $p$-Value |
|---|---|---|---|---|---|---|
| Barley | Sub humid | $Y = 7673.6 \times (\text{average NDVI}^{1.9772})$[a] | 175 | 0.48 | 480.2 | <0.0001 |
| | Semi arid | $Y = 8603.2 \times (\text{average NDVI}^{2.1942})$[b] | 49 | 0.90 | 221.5 | <0.0001 |
| | Arid | $Y = 6706.2 \times (\text{average NDVI}^{1.3703})$[c] | 56 | 0.56 | 389.3 | <0.0001 |
| Canola | Sub humid | $Y = 4307 \times (\text{average NDVI}^{2.1488})$[a] | 175 | 0.49 | 294.4 | <0.0001 |
| | Semi arid | $Y = 5054 \times (\text{average NDVI}^{2.3306})$[b] | 49 | 0.82 | 187.9 | <0.0001 |
| | Arid | $Y = 3419.3 \times (\text{average NDVI}^{1.2797})$[c] | 54 | 0.32 | 322.7 | <0.0001 |
| Field peas | Sub humid | $Y = 8455.2 \times (\text{average NDVI}^{2.8147})$[a] | 162 | 0.53 | 471.3 | <0.0001 |
| | Semi arid | $Y = 11816 \times (\text{average NDVI}^{3.0878})$[b] | 49 | 0.89 | 271.3 | <0.0001 |
| | Arid | $Y = 11967 \times (\text{average NDVI}^{2.3091})$[c] | 56 | 0.71 | 374.6 | <0.0001 |
| Spring wheat | Sub humid | $Y = 7793.9 \times (\text{average NDVI}^{2.3962})$[a] | 160 | 0.47 | 545.7 | <0.0001 |
| | Semi arid | $Y = 6299.4 \times (\text{average NDVI}^{2.0342})$[b] | 49 | 0.80 | 263.5 | <0.0001 |
| | Arid | $Y = 5989.7 \times (\text{average NDVI}^{1.4895})$[c] | 52 | 0.63 | 285.4 | <0.0001 |

SEM = standard error of the mean.
[a] Average NDVI for four dekads from 3rd dekad June to the 3rd dekad August.
[b] Average NDVI for four dekads from 1st dekad July to the 1st dekad August.
[c] Average NDVI for four dekads from 1st dekad July to the 1st dekad August.

infrared 0.841 to 0.876 μm wavelength (Band 2). The presence of chlorophyll pigment in green vegetation and leaf scattering mechanisms cause low spectral reflectance in Band 1 and high reflectance in Band 2, respectively. Reflectance values change in the opposite direction if vegetation is under stress (Kogan, 1994). Hence, the NDVI measures vegetation vigour and greenness (Tarpley et al., 1984) and is calculated as follows:

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}} \tag{1}$$

where NIR and R represent the reflectance of the near infrared (Band 2) and the red (Band 1), respectively. The NDVI is unit-less, with values ranging from −1 to +1. Healthy green vegetation normally has the highest positive values, surfaces without vegetation such as water, snow, ice or clouds usually have negative NDVI values, while rocks bare soil have values close to zero. Stressed vegetation or vegetation with small leaf area has positive but reduced NDVI values (Kogan, 1994; Hayes and Decker, 1996; Basnyat et al., 2004). A typical NDVI temporal profile for healthy green vegetation rises as plant cover increases during spring, reaches a peak during summer and declines during autumn (Baez-Gonzalez et al., 2002). The NDVI relates to the photosynthetic activity of the overall crop (Basnyat et al., 2004; Gu et al., 2008).

A crop cover mask that delineated only those areas under cultivation in western Canada had been previously derived from Landsat TM images (Hochheim, 1995). A copy of the crop cover mask was obtained from the Statistics Canada Crop Condition Assessment Program (Statistics Canada, 2009a) and used to eliminate the influence of non-agricultural and non-annual crops on the NDVI signal. Consequently, all areas with non-agricultural land were masked out and NDVI values were extracted for only those areas having annual crops.

### *2.4. Statistical analysis*

Statistical analysis was done separately for each crop in each agro-climatic zone. As stated earlier, the CARs were categorised into three agro-climatic zones: sub-humid zone, semi-arid zone and arid zone (Fig. 2). Correlation and regression analyses were performed using dekadal composite NDVI values (independent variable) and crop grain yield data (dependent variable) for each CAR within an agro-ecological zone. This resulted in a large number (≥49) of data points for each crop-yield model in each agro-ecological zone (Table 1). In addition, running average NDVI for 2, 3 and 4 dekads with highest correlation coefficients ($r$) were used as independent variables to test if there was an improvement in the correlations. When studying the relationship between NDVI and wheat yield grown on the Canadian Prairie, Hochheim and Barber (1998) found that averaging NDVI using a 3-week running mean increased the coefficient of determination ($R^2$) and stabilised the regression models. Mkhabela et al. (2005) found that using cumulative NDVI (over 3 to 4 dekads) rather than a single average dekadal NDVI value resulted in better regression models for predicting maize yield in Swaziland. Integration of NDVI on a time interval avoids oscillations due to other than vegetation responses, and also takes into account the cumulative effect of photosynthesis (Rudorff and Batista, 1990; Benedetti and Rossini, 1993).

Results from linear, exponential, power and logarithmic models were compared in order to select the best model. Hayes and Decker (1996) found that a quadratic model better explained the relationship between NDVI and corn yield in the US corn-belt. Meanwhile, Benedetti and Rossini (1993) found a linear model to be more suitable for relating NDVI to wheat yield in Italy. Similarly, Rasmusen (1992), Quarmby et al. (1993), Groten (1993), Mkhabela and Mkhabela (2000) and Mkhabela et al. (2005) all found linear models to be more suitable for the different crops they studied. Holzapfel et al. (2009) found that both linear and exponential models were suitable for relating NDVI to canola grain yield, while Ma et al. (2001) found a power function to be more suitable for relating NDVI to soybean grain yield. The contrasting findings show that regression models relating NDVI to crop yield will differ depending on many factors including crop, soil type and environment.

To test the robustness and the ability of the generated regression models to forecast crops grain yield, one year at a time was removed and new regression models were developed i.e., leave-one-year-out approach (Schut et al., 2009). The developed models with one year removed were then used to forecast the crop grain yield for the missing year. The predicted yield for each crop in each CAR was then compared to the actual yield using a Student's $t$-test, with each CAR in each agro-climatic zone being a replication. In addition, the performance of the models was assessed using the root mean square error (RMSE), the mean absolute error (MAE) and the mean bias error (MBE), all of which can be expressed in units of the measured data (Willmott and Matsuura, 2005; Kahimba et al., 2009). The RMSE gives the weighted variations in errors (residual) between the predicted and measured values and was calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - M_i)^2} \tag{2}$$

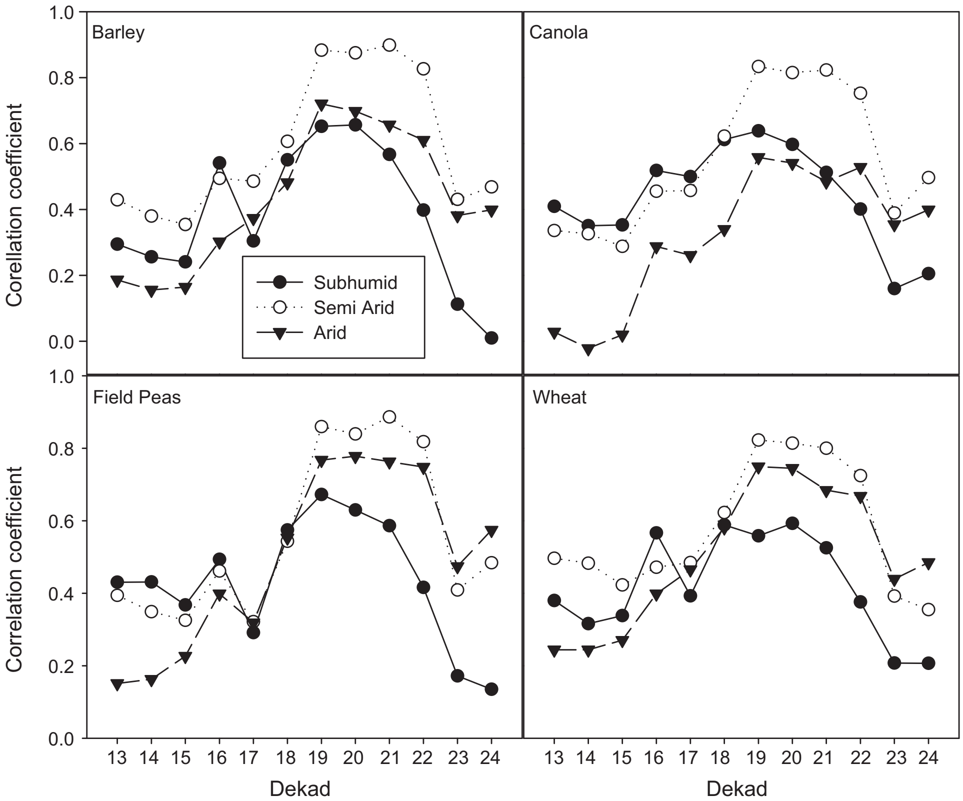


**Fig. 3.** Evolution of the correlation coefficient for NDVI versus barley, canola, field peas and wheat yields in the sub-humid, semi arid and arid agro-climatic zones of the Canadian Prairies from dekad 13 through dekad 24. Note that dekad 13 is the 1st dekad of May, while dekad 24 is the 3rd dekad of August.

where $n$ is the number of observations, $P_i$ is the predicted yield and $M_i$ is the measured yield. The mean absolute error (MAE) measures the weighted average magnitude of the *absolute* errors and was calculated as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|P_i - M_i|$$

where $n$ is the number of observations, $P_i$ is the predicted yield and $M_i$ is the measured yield. According to Willmott and Matsuura (2005) the MAE is the most natural and unambiguous measure of average error magnitude; however, the RMSE is one of the most widely used error measures. Both the RMSE and MAE values were converted to percent RMSE (% RMSE) and percent MAE (% MAE) by dividing the RMSE or MAE by the mean of observed yield.

The MBE is an indicator of whether the model is under predicting or over predicting the measured values and also gives the uniformity of error distribution. Positive MBE values indicate over prediction, negative values indicate under prediction and a value of zero indicates equal distribution between negative and positive values. The MBE was calculated as follows:

$$\mathrm{MBE} = \frac{1}{n}\left[\sum_{i=1}^{n}(P_i - M_i)\right] \tag{3}$$

where $n$ is the number of observations, $P_i$ is the predicted yield and $M_i$ is the measured yield.

## 3. Results and discussion

Fig. 3 shows the evolution (throughout the growing season) of the correlation coefficient ($r$) for the relationship between MODIS-NDVI and crop grain yields in all the agro-climatic zones. In the sub-humid zone the NDVI is highly correlated ($r$ = 0.51 to 0.67) with grain yield (all crops) from dekad 18 through 21 (late June to July), while in the semi-arid and arid zones the highest correlation ($r$ = 0.72 to 0.90 and 0.48 to 0.78, respectively) is from dekad 19 through 22 (early July to early August). In general, these periods coincide with the flowering and grain filling periods of all the crops included in the study. These results are in agreement with previous studies which have reported higher correlation between NDVI and crop yields during the flowering and grain filling period (Unganai and Kogan, 1998; Mkhabela and Mkhabela, 2000; Labus et al., 2002; Mkhabela et al., 2005; Marti et al., 2007; Salazar et al., 2007). When studying the relationship between NDVI and the grain yield of several crops grown on the Canadian Prairie, Basnyat et al. (2004) concluded that the period from 10 to 30 July is the optimum time period for obtaining NDVI information to be related with final crop grain yield for spring-seeded crops. Similarly, Hochheim and Barber (1998) found that NDVI correlated well with wheat yield from week of the year (WOY) 29 through WOY 32. Hayes and Decker (1998) reported that the highest correlation between VCI (derived from NDVI) and corn yield in the USA corn-belt was from WOY 31 through WOY 36, when the corn crop was at silking, dough and dent stages of development. The flowering and grain filling periods are the most critical for most crops; any water stress during these crop growth stages may result in reduced grain yields. Grain yield is influenced most by crop conditions during the heading phase that usually occurs in July in the case of wheat on the Prairies (Boken and Shaykewich, 2002). The results of the current study imply that in the sub-humid zone preliminary grain yield forecasts for all the crops in the study can be made by the end of June, while in the semi-arid and arid zones it can be made by the beginning of July.

For all the crops used in the study and all the agro-climatic zones the relationship between MODIS-NDVI and grain yield was best described by a power function (Figs. 4 to 7), with coefficient

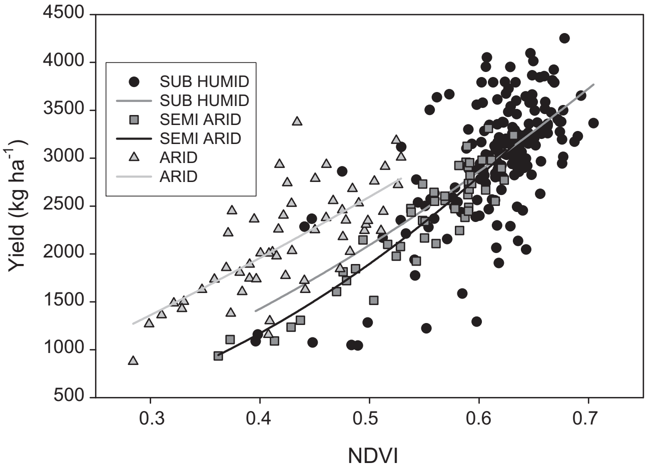


**Fig. 4.** Relationship between barley grain yield and NDVI in the sub humid, semi arid and arid agro-climatic zones of the Canadian Prairies.

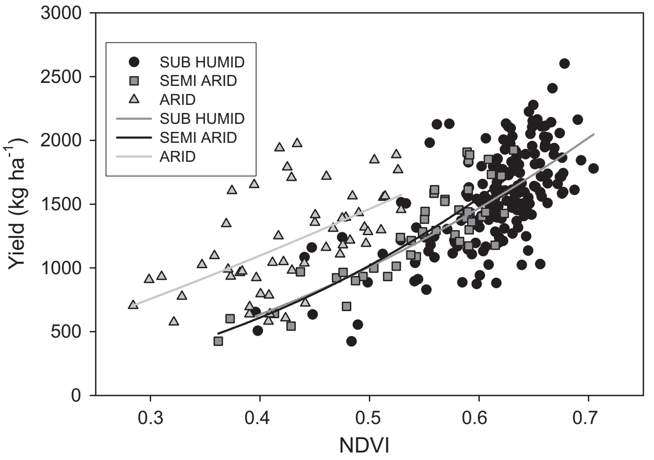


**Fig. 5.** Relationship between canola grain yield and NDVI in the sub humid, semi arid and arid agro-climatic zones of the Canadian Prairies.

of determination ($R^2$) ranging from 0.48 to 0.90 for barley, 0.32 to 0.82 for canola, 0.53 to 0.89 for field peas and 0.47 to 0.80 for wheat (Table 1). This indicates that the developed models explained from 48 to 90%, 32 to 82%, 53 to 89% and 47 to 80% of the variability of barley, canola, field peas and wheat yields, respectively. The models in the current study are comparable to models developed by other researchers relating NDVI to the yield of different crops (e.g., Benedetti and Rossini, 1993; Hayes and Decker, 1996, 1998; Mkhabela and Mkhabela, 2000; Mkhabela et al., 2005; Marti et al., 2007; Becker-Reshef et al., 2010). On the Canadian Prairies, Bullock (1992) and Wall et al. (2008) obtained $R^2$ values of 0.60 and ~0.55 respectively, when relating AVHHR-NDVI to wheat grain yield. In Saskatchewan, Basnyat et al. (2004) studied the relationship between NDVI and crop grain yield and reported $R^2$ values of 0.49 for peas, 0.18 for canola and 0.42 for wheat. In a study conducted in Manitoba, Saskatchewan and Ontario, Holzapfel et al. (2009) found that NDVI correlated significantly with canola seed yield with $R^2$ ranging from 0.36 to 0.43.

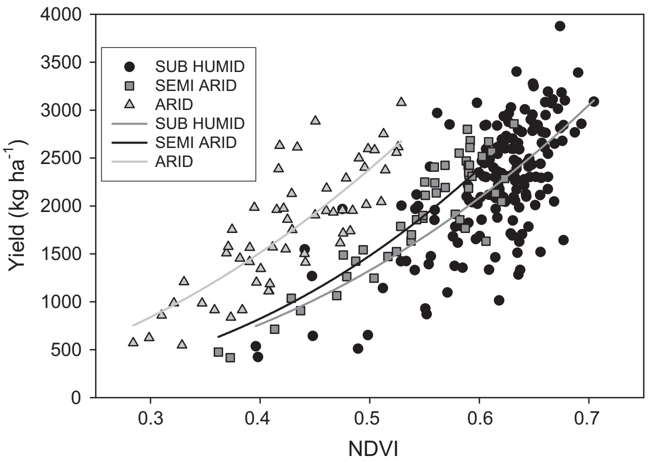


**Fig. 6.** Relationship between field peas grain yield and NDVI in the sub humid, semi arid and arid agro-climatic zones of the Canadian Prairies.

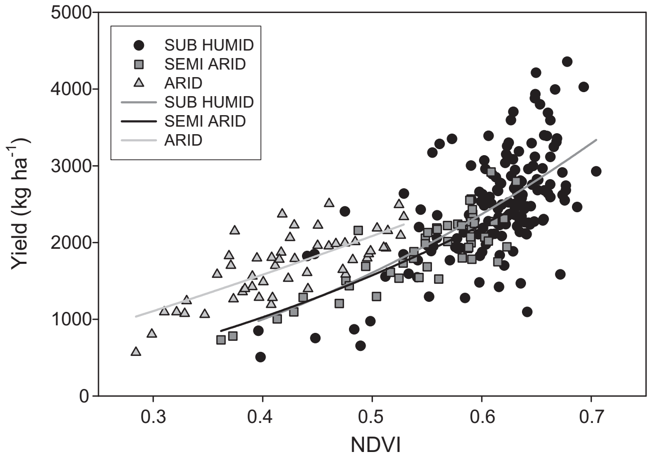


**Fig. 7.** Relationship between spring wheat grain yield and NDVI in the sub humid, semi arid and arid agro-climatic zones of the Canadian Prairies.

Generally, for all the crops the best prediction models were in the semi-arid zone with $R^2$ ranging from 0.80 to 0.90, followed by the arid zone with $R^2$ ranging from 0.32 to 0.71 and lastly the sub-humid zone with $R^2$ ranging from 0.47 to 0.53 (Table 1). The slightly lower $R^2$ in the sub-humid zone most likely indicates that moisture is of lesser importance to crop yield in this zone. The sub-humid zone receives the highest average annual precipitation compared to the other two zones (DePauw et al., 2011). Mkhabela et al. (2005) found that the relationship between AVHHR-NDVI and maize yield in Swaziland was poor in high rainfall areas. In Western Australia, Hill and Donald (2003) reported that the correlation between agricultural productivity and time integrated NDVI was low during wet years. The authors reported a maximum rainfall threshold of 600 mm above which the relationship between agricultural productivity and NDVI was negative. It is interesting to note that the relationship between MODIS-NDVI and crop yield is lower in the arid zone compared to the semi-arid zone. This is most likely due to the higher prevalence of summer fallow in the arid zone. Hochheim and Barber (1998) reported that NVDI profiles in the Canadian Prairie are indicative of soil moisture and agronomic practices, especially summer-fallow. The authors concluded that percent summer fallow is an important stratification variable when defining spectrally homogeneous CARs and therefore it should be considered when establishing the relationship between NDVI and crop yield. In the current study we were unable to separate/remove areas under summer fallow and this might have affected the NDVI profiles, particularly in the arid zone where this practice is most prevalent.

In the arid zone the relationship between MODIS-NDVI and canola yield was the poorest ($R^2 = 0.32$), although this $R^2$ value is similar to that observed by Holzapfel et al. (2009) ($R^2 = 0.32$ to 0.45), but higher than that observed by Basnyat et al. (2004) ($R^2 = 0.18$). The lower correlation is probably due to the fact that canola represents a small fraction of the total crop area in the arid zone, and yet, the NDVI is an average of all the crops grown in the region. Even though we were able to mask-out (remove) non-crop areas, it was not possible to extract NDVI for each specific crop. In other words, the NDVI is representative of all the crops in the area and thus it will be highly influenced by dominant crops, making it less correlated to non-dominant crops. In Italy, Benedetti and Rossini (1993) found that correlation between AVHHR-NDVI and wheat yield was poor in areas where wheat was not a dominant crop and attributed this to weak radiometric dominance of the wheat crop. New techniques are however, being developed to discriminate crop types and crop-related land use practices such as summer fallow using MODIS-NDVI data (e.g., Maselli and Rembold, 2001; Kastens et al., 2005; Wardlow et al., 2007, 2008), and this will hopefully result in improved crop yield prediction models.

Another factor that may have contributed to the lower correlation between MODIS-NDVI and canola yield in the arid zone is the impact of high temperature on canola during flowering, which may not be clearly detected by the NDVI. A combination of high temperatures >30 °C and low precipitation during the flowering and seed-filling stages significantly decreases canola yield (Nuttall et al., 1992; Chen et al., 2005; Kutcher et al., 2010). In southern Ontario, Warland et al. (2006) found a negative correlation between the number of days with temperature >30 °C and the yield of five *Brassica* spp. vegetable crops. According to Kutcher et al. (2010), there is a 12% reduction in canola grain yield for every 7 days of maximum temperature >30 °C. On average, the arid zone experiences maximum temperature >30 °C for 14 to 24 days per year (DePauw et al., 2011).

The ability of the developed models to predict crop grain yield was tested using the leave-one-year-out procedure. Table 2a shows the predicted and actual grain yield and the percent difference of the predicted yield from the actual yield for all the crops in all the agro-climatic zones. Overall, the % difference of the predicted from actual yield is within 10% and statistically not significantly different ($p > 0.05$). For barley the % difference is within 7% except for 2002, 2004 and 2005 when it is within 16% in the sub-humid and arid zones, while for canola it is within 16% except for 2003 and 2004 when it is within 53% and 24%, respectively, in the arid zone. For field peas the difference is within 15% except for 2002 when it is within 20% in both the sub humid and semi arid zones. Meanwhile, for spring wheat the difference is within 15% except for 2001 and 2002 when it is within 18% in the sub humid zone. These differences between predicted and actual grain yield are similar to those recorded by Benedetti and Rossini (1993) when correlating AVHRR-NDVI and wheat yield in Italy. In the USA, Doraiswamy et al. (2005) when relating MODIS-NDVI and crop yield (corn and soybean) reported yield differences within 10% of the actual yield. In Australia, Schut et al. (2009) reported yield differences of 10% between predicted and actual yield when correlating MODIS-NDVI and wheat yield, while in China, Ren et al. (2008) reported yield differences between predicted and actual yield ranging from −4.6% to 5.4% when correlating MODIS-NDVI and wheat yield.

Table 2b shows the root mean square errors (RMSE), the mean absolute error (MAE) and the mean bias error (MBE) for all the crops in all the agro-climatic zones. For barley the RMSE ranged from 351 to 654, 150 to 258 and 184 to 584 while for canola it ranged from 189 to 403, 108 to 273 and 173 to 475 kg ha$^{-1}$ in the sub-humid, semi-arid and arid zones, respectively. Meanwhile for field peas it ranged from 363 to 677, 204 to 547 and 256 to 575, while for spring wheat it ranged from 463 to 697, 104 to 382 and 191 to 365 kg ha$^{-1}$ in the sub-humid, semi-arid and arid zones, respectively. Ren et al. (2008) reported a RMSE value of 214 kg ha$^{-1}$ when correlating MODIS-NDVI data with wheat grain yield in China, while Moriondo et al. (2007) reported RMSE values of 440 and 470 kg ha$^{-1}$ when developing a wheat yield prediction model using AVHRR-NDVI data in

**Table 2a**
Comparison of predicted to actual crop grain yield in all the agro-climatic zones on the Canadian Prairies.

| Crop | Year | Sub humid | | | | Semi arid | | | | Arid | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Predicted (kg ha$^{-1}$) | Actual (kg ha$^{-1}$) | Diff. (%) | *p*-Value | Predicted (kg ha$^{-1}$) | Actual (kg ha$^{-1}$) | Diff. (%) | *p*-Value | Predicted (kg ha$^{-1}$) | Actual (kg ha$^{-1}$) | Diff. (%) | *p*-Value |
| Barley | 2000 | 3214.4 | 3172.4 | +1.3 | 0.56 | 2654.5 | 2530.0 | +4.9 | 0.12 | 2251.6 | 2298.0 | −2.0 | 0.64 |
| | 2001 | 2858.9 | 2722.8 | +5.0 | 0.21 | 2135.2 | 2028.4 | +5.3 | 0.28 | 1703.1 | 1590.0 | +7.1 | 0.08 |
| | 2002 | 2341.0 | 2684.4 | +14.7 | <0.01 | 1728.7 | 1615.0 | +7.0 | 0.25 | 1901.8 | 1691.0 | +12.5 | 0.06 |
| | 2003 | 2962.5 | 3169.0 | −6.5 | <0.01 | 1914.3 | 1977.0 | −3.2 | 0.30 | 1947.6 | 1765.0 | +10.4 | 0.26 |
| | 2004 | 2919.7 | 3465.9 | −15.8 | <0.01 | 2653.9 | 2821.1 | −5.9 | 0.08 | 2401.8 | 2759.6 | −13.0 | 0.03 |
| | 2005 | 3023.5 | 2829.6 | +6.9 | 0.12 | 2855.8 | 2891.6 | −1.2 | 0.72 | 2384.9 | 2717.6 | −12.2 | 0.11 |
| | 2006 | 3012.1 | 3221.5 | −6.5 | 0.02 | 2422.1 | 2601.0 | −6.9 | 0.02 | 2077.7 | 2100.0 | −1.0 | 0.88 |
| Canola | 2000 | 1715.2 | 1473.2 | +16.4 | <0.01 | 1440.2 | 1426.0 | +1.0 | 0.80 | 1220.3 | 1342.0 | −9.1 | 0.18 |
| | 2001 | 1478.0 | 1378.4 | +7.2 | 0.06 | 1161.1 | 1047.1 | +10.9 | 0.27 | 944.6 | 882.9 | +7.0 | 0.35 |
| | 2002 | 1335.7 | 1297.0 | +3.0 | 0.31 | 911.7 | 872.0 | +4.6 | 0.37 | 1068.0 | 971.0 | +10.1 | 0.46 |
| | 2003 | 1541.7 | 1596.0 | −3.4 | 0.22 | 1061.8 | 945.0 | +12.3 | 0.02 | 1141.3 | 748.0 | +52.5 | <0.01 |
| | 2004 | 1538.6 | 1650.4 | −6.8 | 0.17 | 1474.9 | 1448.4 | +1.8 | 0.69 | 1265.6 | 1666.4 | −24.1 | <0.01 |
| | 2005 | 1530.1 | 1667.1 | −8.2 | 0.07 | 1528.4 | 1721.1 | −11.2 | 0.05 | 1299.5 | 1479.3 | −12.2 | 0.20 |
| | 2006 | 1537.5 | 1805.4 | −14.8 | <0.01 | 1297.9 | 1528.0 | −15.0 | <0.01 | 1124.7 | 1283.0 | −12.3 | 0.19 |
| Field peas | 2000 | 2476.8 | 2465.7 | +0.5 | 0.89 | 2202.3 | 2344.4 | −6.1 | 0.22 | 1892.4 | 2125.5 | −11.0 | 0.09 |
| | 2001 | 2061.6 | 2031.9 | +1.5 | 0.75 | 1698.5 | 1620.6 | +4.8 | 0.37 | 1275.2 | 949.4 | +34.3 | 0.10 |
| | 2002 | 1907.3 | 1601.3 | +19.1 | <0.01 | 1362.0 | 1132.7 | +20.2 | <0.01 | 1396.9 | 1434.5 | −2.6 | 0.77 |
| | 2003 | 2203.3 | 2263.7 | +2.7 | 0.43 | 1423.3 | 1516.3 | −6.1 | 0.26 | 1454.7 | 1415.0 | +2.8 | 0.82 |
| | 2004 | 2164.6 | 2624.1 | −17.5 | <0.01 | 2263.5 | 2455.7 | −7.8 | 0.02 | 2162.2 | 2544.3 | −15.0 | 0.05 |
| | 2005 | 2313.3 | 2197.9 | +5.2 | 0.43 | 2595.5 | 2324.7 | +11.6 | 0.21 | 2210.5 | 2213.4 | −0.12 | 0.99 |
| | 2006 | 2219.0 | 2482.6 | −10.6 | <0.01 | 1996.5 | 2151.4 | +7.2 | 0.07 | 1996.5 | 1646.4 | +2.6 | 0.74 |
| Spring wheat | 2000 | 2768.6 | 2651.4 | +4.4 | 0.34 | 2119.2 | 2036.0 | +4.1 | 0.50 | 1858.2 | 1868.0 | −0.5 | 0.63 |
| | 2001 | 2383.7 | 2033.0 | +17.2 | 0.01 | 1724.5 | 1705.6 | +1.1 | 0.91 | 1363.6 | 1265.0 | +7.8 | 0.16 |
| | 2002 | 2169.0 | 1846.0 | +17.5 | <0.01 | 1474.1 | 1290.0 | +14.3 | 0.01 | 1514.9 | 1450.0 | +4.5 | 0.55 |
| | 2003 | 2458.7 | 2650.0 | −7.2 | 0.05 | 1632.6 | 1652.0 | −1.2 | 0.66 | 1543.3 | 1484.0 | +4.0 | 0.27 |
| | 2004 | 2394.5 | 2863.1 | −16.4 | <0.01 | 2148.4 | 2123.4 | +1.2 | 0.85 | 2001.9 | 2150.3 | −6.9 | 0.23 |
| | 2005 | 2443.2 | 2601.5 | −6.1 | 0.19 | 2255.9 | 2329.0 | −3.1 | 0.50 | 2096.7 | 2148.5 | −2.4 | 0.72 |
| | 2006 | 2464.4 | 2792.0 | −11.7 | <0.01 | 1934.0 | 2143.0 | +9.8 | <0.01 | 1669.2 | 1757.0 | −5.0 | 0.53 |

**Table 2b**
Comparison of predicted to actual grain yield in all agro-climatic zones on the Canadian Prairies.

| Crop | Year | Sub humid | | | Semi arid | | | Arid | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RMSE (kg ha$^{-1}$)[a] | MAE (kg ha$^{-1}$)[a] | MBE (kg ha$^{-1}$) | RMSE (kg ha$^{-1}$)[a] | MAE (kg ha$^{-1}$)[a] | MBE (kg ha$^{-1}$) | RMSE (kg ha$^{-1}$)[a] | MAE (kg ha$^{-1}$)[a] | MBE (kg ha$^{-1}$) |
| Barley | 2000 | 351(11) | 253(8) | 42 | 210(8) | 170(7) | 125 | 260(11) | 216(9) | −47 |
| | 2001 | 541(19) | 410(15) | 136 | 245(12) | 204(10) | 107 | 184(12) | 130(8) | 113 |
| | 2002 | 508(22) | 398(17) | 344 | 248(15) | 204(13) | 113 | 328(19) | 235(14) | 211 |
| | 2003 | 360(11) | 274(9) | −207 | 150(8) | 118(6) | −623 | 439(25) | 317(18) | 183 |
| | 2004 | 654(19) | 552(16) | −546 | 258(9) | 207(7) | −167 | 496(18) | 399(15) | −358 |
| | 2005 | 626(22) | 482(17) | 194 | 238(8) | 206(7) | −36 | 584(22) | 472(17) | −333 |
| | 2006 | 447(14) | 317(10) | −209 | 230(9) | 185(7) | −179 | 379(18) | 289(14) | −22 |
| Canola | 2000 | 323(22) | 281(19) | 242 | 140(10) | 113(8) | 15 | 247(18) | 166(12) | −122 |
| | 2001 | 270(20) | 220(16) | 100 | 259(25) | 206(20) | 114 | 173(20) | 147(17) | 62 |
| | 2002 | 188(15) | 145(11) | 39 | 108(12) | 77(9) | 40 | 291(30) | 236(24) | 98 |
| | 2003 | 219(14) | 183(11) | −55 | 154(16) | 130(14) | 117 | 437(58) | 393(53) | 393 |
| | 2004 | 403(24) | 349(21) | −112 | 156(11) | 139(100 | 27 | 475(29) | 401(24) | −401 |
| | 2005 | 385(23) | 313(19) | −137 | 273(16) | 220(13) | −193 | 380(26) | 287(19) | −180 |
| | 2006 | 321(18) | 268(15) | −268 | 258(17) | 230(15) | −130 | 328(26) | 248(19) | −158 |
| Field peas | 2000 | 385(16) | 295(12) | 11 | 290(12) | 261(11) | −142 | 393(19) | 304(14) | −233 |
| | 2001 | 451(22) | 377(19) | 30 | 212(13) | 134(8) | 78 | 359(38) | 330(35) | 319 |
| | 2002 | 498(31) | 386(24) | 306 | 243(22) | 229(20) | 229 | 345(24) | 315(22) | −51 |
| | 2003 | 363(16) | 271(12) | −60 | 204(14) | 175(12) | −93 | 256(18) | 211(15) | 30 |
| | 2004 | 602(22) | 506(19) | −460 | 237(10) | 196(98) | −192 | 575(23) | 437(17) | −382 |
| | 2005 | 677(31) | 589(27) | 115 | 547(24) | 451(19) | 271 | 422(19) | 347(16) | −3 |
| | 2006 | 414(17) | 316(13) | −264 | 230(11) | 185(9) | −155 | 335(20) | 280(17) | 43 |
| Spring wheat | 2000 | 583(22) | 473(18) | 117 | 294(15) | 262(13) | 83 | 266(14) | 250(13) | −59 |
| | 2001 | 697(34) | 565(28) | 351 | 382(22) | 276(16) | 19 | 191(15) | 151(12) | 99 |
| | 2002 | 462(25) | 399(22) | 323 | 218(17) | 199(15) | 184 | 259(18) | 213(15) | 16.3 |
| | 2003 | 463(18) | 324(12) | −191 | 104(6) | 96(6) | −19 | 224(15) | 183(12) | 58.9 |
| | 2004 | 714(25) | 557(19) | −469 | 308(15) | 254(12) | 25 | 358(16) | 266(12) | −148.4 |
| | 2005 | 576(22) | 438(17) | −158 | 258(11) | 223(10) | −73 | 309(14) | 248(12) | −51.8 |
| | 2006 | 498(18) | 383(14) | −328 | 249(12) | 209(10) | −209 | 365(21) | 282(16) | −87.6 |

[a] Numbers in brackets are percentages (i.e., percent error).

two Italian provinces. The MAE values followed a similar trend as the RMSE but were slightly lower. Overall, there was an equal distribution of positive and negative MBE values, suggesting that in half of the cases the models over predicted crop grain yield (Table 2b). In all the agro-climatic zones the models generally over predicted crop yield in 2000 and 2002 and under predicted crop yield in 2003 and 2006.

## 4. Conclusion

This study has shown that MODIS-NDVI can be used effectively to predict crop yields across the Canadian Prairies one to two months before harvest; however, preliminary crop yield forecasts can be made by late June in the sub-humid zone and by early July in the semi-arid and arid zones. Depending on the agro-climatic zone, the models accounted for 48 to 90%, 32 to 82%, 53 to 89% and 47 to 80% of the yield variability of barley, canola, field peas and spring wheat, respectively. In general, the predicted yields were ±10% of the actual observed yields, with RMSE values for barley, canola, field peas and spring wheat ranging from 150 to 654, 108 to 475, 204 to 677 and 104 to 714 kg ha$^{-1}$, while the MAE values ranged from 118 to 552, 77 to 401, 175 to 589 and 96 to 556 kg ha$^{-1}$, respectively.

Although the developed models show some promise in crop yield forecasting on the Canadian Prairie, it has to be noted that all models have limitations. The NDVI measures potential yield; therefore, anything that happens to the crop after the forecast date is not reflected in the crop yield estimate. For example, if a drought, disease or pests outbreak happens after the forecast date the models would most likely overestimate crop yield. In addition, satellite images are affected by various atmospheric effects e.g., clouds and volcano eruptions, which in turn reduce the quality of the data acquired and subsequently the developed crop-yield models.

Owing to the limited number of years used in the current study, the developed models have to be constantly updated as both MODIS-NDVI and crop yield data become available. In addition, it has been shown that spring wheat yields on the Canadian Prairies can be forecast from indicators related to water stress (Qian et al., 2009), and water demand and water balance (Mkhabela et al., 2010) at different crop stages. Meanwhile, Boken and Shaykewich (2002) combined a wheat yield model with NDVI to improve wheat yield predictions in Saskatchewan. Vicente-Serrano et al. (2006) combined NDVI and SPI, while Rojas (2007) combined the FAO crop specific water balance model with NDVI and meteorological data to improve crop yield forecasting in Spain and Kenya, respectively. Similarly, Prasad et al. (2006) developed two models that combined NDVI, soil moisture, surface temperature and rainfall data to forecast maize and soybean yield in Iowa, USA, while Balaghi et al. (2008) developed models that combined NDVI, rainfall and air temperature to forecast wheat yield in Morocco. All these studies reported improvements in crop yield predictions. Therefore, there is the possibility of combining MODIS-NDVI data with climatological data, such as, the Standardised Precipitation Index (SPI) and evapotranspiration (ET) to improve the performance of the models, which is an obvious next step to be explored.

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