Spring Wheat Yield Assessment under Drought Conditions Using Vegetation Health Index: Case of Canadian Prairies

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Abstract

Agricultural drought is a major climate concern which occurs frequently on Canadian prairies. It acts negatively on crop production, which directly affects the Canadian economy. The Normalized Difference Vegetation Index (NDVI) has been widely used to assess crop yield losses related to drought events. However, this index suffers from some shortcomings such as the apparent time lag between drought impact due to rainfall deficit and NDVI response. This study was undertaken to investigate the effectiveness of the integrated Vegetation Health Index (iVHI) for the assessment of spring wheat yield across Canadian prairies. A time series of five years from the Advanced Very High Resolution Radiometer (AVHRR) sensor were used to develop a spring wheat yield model for three agroclimatic regions: subarid, semiarid and subhumid. The results demonstrated that spring wheat yield assessment is feasible through the use of iVHI, especially in subarid and semiarid regions where it reached a correlation coefficient of 0.75 and 0.61, respectively. This finding shows that iVHI can be used to estimate spring wheat yield losses due to agricultural drought across the Canadian prairies. However, in subhumid regions where spring wheat growing conditions are favourable because of adequate water supply, the integrated NDVI (iNDVI) outperforms iVHI with a correlation coefficient of 0.44 compared to 0.34. Consequently, to develop an efficient tool, it suggested coupling the iVHI with iNDVI to better estimate spring wheat yield in the Canadian prairies.

Keywords: Spring wheat, drought, yield assessment, AVHRR, NDVI, vegetation health index.

1. Introduction

The major factor that limits agricultural productivity across the Canadian prairies is the dry climate with frequent drought events. Their impact on agriculture can be gradual and cumulative, and in some cases occur so slowly that they are not easily discernable. As a result of agricultural drought, crop production is reduced, which directly affects the Canadian economy. A preliminary analysis of the 2001 and 2002 drought years on the Prairies indicated that agricultural production sales dropped to \$3.6 billion, with the largest loss occurring in 2002 at more than \$2 billion (Wheaton *et al.* 2005). Spring wheat, hereafter referred to as wheat, is the dominant crop on the Canadian prairies, with approximately 75% of its total production exported through the Canadian Wheat Board (CWB) (Kumar 1999). In the 2001 and 2002 drought years, wheat production dropped by approximately 25% across the Canadian prairies (Statistics Canada 2002). In order to develop efficient wheat marketing strategies, assess population demand, and plan existing resources, early accurate wheat yield estimates are required. Currently, the CWB uses a weather-based short term model to forecast wheat yields across the Prairies (Hochheim 1995). This model employs monthly precipitation and temperature data recorded at weather-stations to determine an average cumulative moisture index which is regressed against the average wheat yield for the Prairies. However, weather data often comes from sparse meteorological networks or are not always available in a timely manner to allow an accurate and up-to-date wheat yield assessment. Recent advances in the application of operational satellites such as the National Oceanic and Atmospheric Administration (NOAA) equipped with the Advanced Very High Resolution Radiometer (AVHRR) sensor have proven that the AVHRR-derived Normalized Difference Vegetation Index (NDVI) is an excellent tool for crop conditions and yield assessment. In spite of its usefulness in agriculture, NDVI suffers from some shortcomings for crops monitoring under drought conditions (Wang *et al*. 2001).

Kogan (1995) has developed a method which has been shown to be very useful in arid and semiarid conditions. The Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI) he proposed are found to be dependant on the vegetation, weather and ecological conditions (Singh *et al.* 2003), and more sensitive for crop yield estimates (Unganai and Kogan, 1998; Dabrowska-Zielinska *et al*. 2002; Domenikiotis *et al*. 2004). Liu *et al*. (2002) and Kogan *et al.* (2005) also found that the Vegetation Health Index (VHI) which combines contribution of the VCI and TCI is an effective tool in estimating productivity of crops and pastures, and can be used as an indicator of agricultural losses related to drought. In the present paper, we discuss the potential of the Vegetation Health Index in estimating wheat yield under drought for different agroclimatic regions of the Canadian prairies. The NDVI was also investigated for comparison purposes.

2. Study Area

The Canadian prairies extend northwards from 49^o N (Canada-US border) to 54^o N, and east-west from eastern Manitoba, across Saskatchewan to western Alberta (Figure 1). Topographically, the prairies are a large area of relatively flat sedimentary land stretching throughout western Canada between the Canadian Shield in the east and the Canadian Rockies. The Canadian prairies regions soils are dominated by brown soils in southern Saskatchewan and Alberta, dark brown soils occur in a broad arc through Saskatchewan and Alberta, and black soils from southern Manitoba through mid-central Saskatchewan to western Alberta (Hochheim 1995). These soils are typical of subarid, semiarid and subhumid continental climates respectively. The productivity of subarid regions is severely limited by moisture deficits during the growing season. Semiarid regions are dominated by moderately to severe annual soil moisture deficits, while subhumid areas are characterized by low soil moisture deficit. Spring wheat is the dominant crop on the Prairies with 48% grown in the subhumid regions, 32% in the semiarid regions and the less cropped areas are the subarid regions with only 19%. Statistics Canada compiled crops statistics based on Census Agricultural Regions (CARs) covering the wheat growing regions. The official Statistics Canada yields and levels of production by province are estimated before harvest based on field survey (Statistics Canada, 2002).

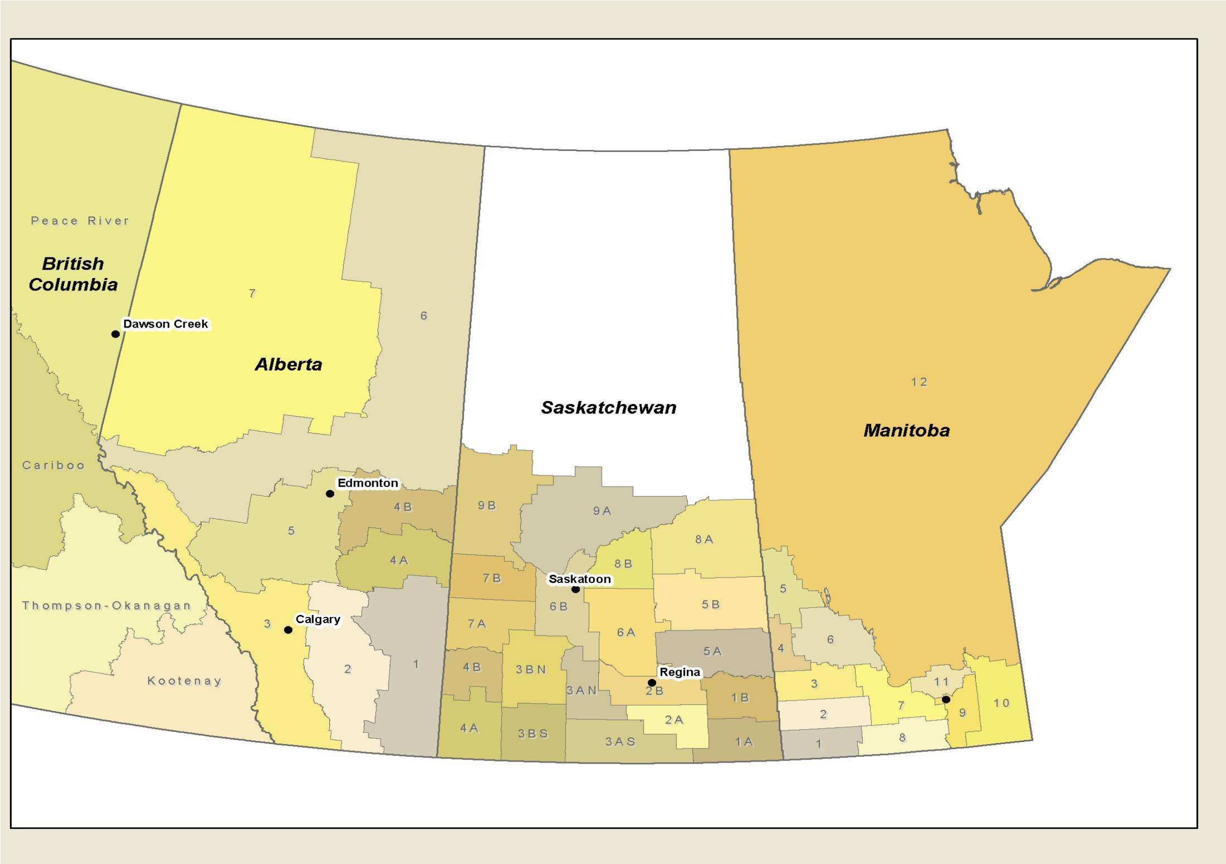

Figure 1: Map of the Canadian Prairies showing the Census Agricultural Regions (CARs)

3. Methods

3.1 NOAA/AVHRR Data

The NOAA/AVHRR sensor collects data in five spectral channels, and three of those have been used in this study to calculate the vegetation indexes. The channels used are the red (0.58-0.68 µm), the near infrared (0.725-1.10 µm) and the thermal channel (10.3-11.3 µm). Five years of data (2001-2005) with a 1-km spatial resolution were processed and geometrically registered to the Lambert conformal conic projection by the Canadian Center of Remote Sensing (CCRS) using the AVHRR data processing system called Earth Observation Data Manager (EODM) (Latifovic *et al*. 2005). In order to minimize cloud effects and haze contamination, the data were composited over a 10-day period by saving those radiances that had the largest difference between the visible and near infrared. Residual cloudy and hazy pixels remaining in the images were detected and corrected by comparing the previous and next composite NDVI values to the current NDVI for the same location. If a sudden drop was followed by sudden increase, the pixel was corrected to the average value of the preceding and the following image composite based on a specific threshold value. In addition to cloud masking, high frequency noise in the 10-day composites was removed by applying a 3 x 3 median filter to the yearly times series data. From these processed composites, the NDVI was calculated using the equation 1:

$$NDVI = \frac{Ch_2 - Ch_1}{Ch_2 + Ch_1} \quad (1)$$

Where Ch_1 and Ch_2 are the near-infrared and red channels, respectively.

Kogan (1997) suggested the use of Vegetation Health Index (VHI) which characterizes soil moisture and thermal conditions based on the combined contributions of the Vegetation Condition Index (VCI) and Temperature Condition Index (TCI). It varies in the range of 0 and 1 with higher values corresponding to favourable soil moisture and unstressed vegetation (non-drought conditions). The VHI algorithm is given by the equation 2:

$$VHI_i = 0.5VCI_i + 0.5TCI_i \quad (2)$$

With

$$VCI_i = \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (3)$$

And

$$TCI_i = \frac{BT_{max} - BT_i}{BT_{max} - BT_{min}} \quad (4)$$

Where $NDVI_i$, $NDVI_{max}$ and $NDVI_{min}$ are the seasonal 10-day NDVI and its multi-years absolute maximum and minimum, respectively, while BT_i, BT_{max} and BT_{min} are the seasonal 10-day brightness temperature, its multi-years absolute maximum and minimum, respectively.

The main idea behind the VCI and indirectly VHI is that it separates the short-term weather-related NDVI fluctuations from the long-term ecosystem changes (Kogan 1995, 1997). For a specific location for example, the maximum amount of vegetation corresponds to years of optimal weather conditions, while the minimum vegetation amounts develop in years with extremely unfavourable weather. This means that the absolute maximum and minimum of NDVI values computed over several years contain the extreme weather events (non-drought conditions and drought conditions), which can be used as criteria for quantifying contributions of geographical areas (non-weather effects). Therefore, for a given 10-day period, this index is a measurement of the impact of weather alone on the local wheat vegetation. The use of TCI in the vegetation health index allows determining temperature-related vegetation stress and also stress caused by excessive wetness (Singh *et al*. 2003). TCI is based on the thermal channel 4 (Ch 4) radiances converted to brightness temperature (BT). The channel Ch 4 was selected because its measured radiance is more representative of drought conditions and less sensitive to the amount of water vapour in the atmosphere compared to the channel 5 (Kogan 1995).

3.2 Wheat Yield Model Development

Since the amount of yield produced at the end of the season depends on cumulative weather impacts, several studies successfully used the integral of vegetation indexes to assess crop conditions and yield (Tucker *et al.* 1985, Hochheim 1995). For instance, Tucker *et al.* (1985) showed that the integral of NDVI provides a reasonably good estimate of the total above ground biomass accumulated during the rainy season. Rasmussen (1992) demonstrated that by limiting the integral of the NDVI to the maximum reproductive phase of millet, yield could be estimated from regression models. The main conclusion drawn by these studies is that integrating a number of NDVI observations appear to be more robust than single date estimates. In fact, integration accounts for both the magnitude and duration of the photosynthetic activity of the crop during the growing cycle (Hochheim, 1995). Therefore, in the current study, we applied the integration approach to the VHI and NDVI. The data were aggregated to the CAR level and averaged to extract VHI and NDVI values for each CARs from 2001 to 2005. The wheat yield was normalized by dividing each agroclimatic region yield by the average yield for that region over the five years period. The resulting linear regression model between normalized wheat yield and integrated vegetation index per agroclimatic region is expressed by equation 5:

$$Yield = a + b\int_{w_1}^{w_2} VHI(t)dt \qquad (5)$$

Where w_1 and w_2 represent the beginning and the end of the critical reproductive phase, a and b are constants determined by regression analysis, and *(t) dt* represent each 10-day period. Models were developed for each agroclimatic region using 75% of the dataset, and wheat yields were estimated based on the remaining randomly selected 25%. The accuracy of wheat yield models was evaluated using the Mean Absolute Error (MAE) as defined by equation 6 (Willmot 1992):

$$MAE = \frac{\sum_{i=1}^{n} \left| y_p - y_o \right|}{n} \qquad (6)$$

Where y_p and y_o are the estimated and Statistics Canada reported wheat yields, respectively and n is the number of observations used for models development. In this study, a technological trend variable was not included in the developed models because of the relatively short five years study period.

4. Results

4.1 Vegetation indexes temporal profiles

Table 1 shows the average wheat yield calculated over the five years periods for each agroclimatic regions. As expected, the highest wheat yield was encountered in the subhumid regions where crop growing conditions are favourable, while subarid regions are characterized by the lower yield. These differences in wheat yield are related to the difference in growing conditions due to high variability of rainfall and temperature conditions on the Canadian prairies. Figure 2 shows temporal profiles of NDVI values during the wheat growing season from 10-day periods 11 to 26 (late April to late September). For all agroclimatic regions, the NDVI increased steadily towards a well-defined maximum, thought to be determined by the reproductive phase of the wheat crop, and was then followed by a subsequent decrease. The maximum NDVI value of 0.54 was reached at 10-day period 19 in subhumid regions, while for semiarid and subarid regions the maximum NDVI values of 0.47 and 0.37 were reached ten days later (at 10-day period 20), respectively. Figure 2 also indicates that differences in wheat growing conditions between agroclimatic regions during the season are well captured by the NDVI. The NDVI temporal pattern is consistent with wheat yield variation as illustrated in Table 1. The higher

NDVI values occurred in subhumid regions associated with favourable growing conditions, while subarid regions dominated by severe soil moisture deficits have the lower NDVI values.

Table 1. Average wheat yield over five years period

Agro-climatic regions	Minimum (bu/ac)	Maximum (bu/ac)	Mean (bu/ac)
Subarid	7.54	37.30	25.30
Semiarid	8.42	49.80	28.40
Subhumid	10.86	64.80	36.30

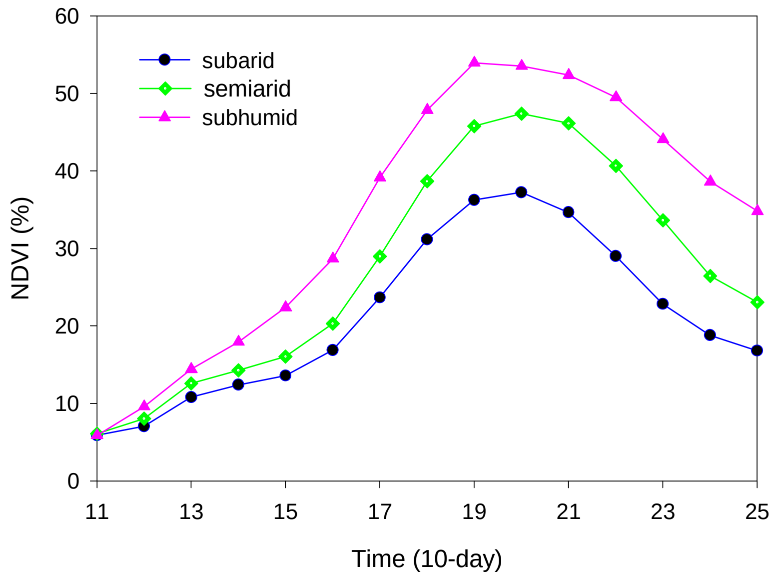

Figure 2: Five years time-series NDVI temporal profiles in the agroclimatic regions

The temporal profiles of VHI during the wheat growing season indicate that until the 10-day period 17, the weather conditions highly fluctuated on the Canadian prairies (Figure 3). The VHI values in subarid regions were below 50% for most of the growing season, suggesting less favourable growing conditions. The lower VHI values can be explained by the influence of 2001 and 2002 drought events. Indeed, during these years, a mix of dry, windy, below-normal precipitation and cooler temperature were observed across the Canadian prairies (Statistics Canada, 2002). This pattern persisted throughout the spring season, causing delays in wheat seeding and plants emergence across the Prairies. The gradual increases observed in VHI values between 10-day periods 17 and 23 for semiarid and subhumid regions, and between 10-day periods 18 and 23 for subarid regions are explained by the fact that most Prairies regions received timely rainfall during the critical reproductive phase of wheat. Therefore, the wheat crop was rated as being in good to excellent condition during 2003, 2004 and 2005 years, and yield potential was above the average due to adequate rainfall and lack of heat stress. These observations show that the VHI dynamic is consistent with the weather conditions recorded across the Prairies during 2001-2005 cropping season. The steepest decrease in VHI values at the 10-day period 24 suggests deterioration in weather conditions latter in the season, probably due to heavy rainfall events prior to harvest time. Comparison of Figures 2 and 3 clearly show that changes in VHI profiles due to weather-related fluctuations from year to year are not directly captured by NDVI which mainly reflects vegetation greenness.

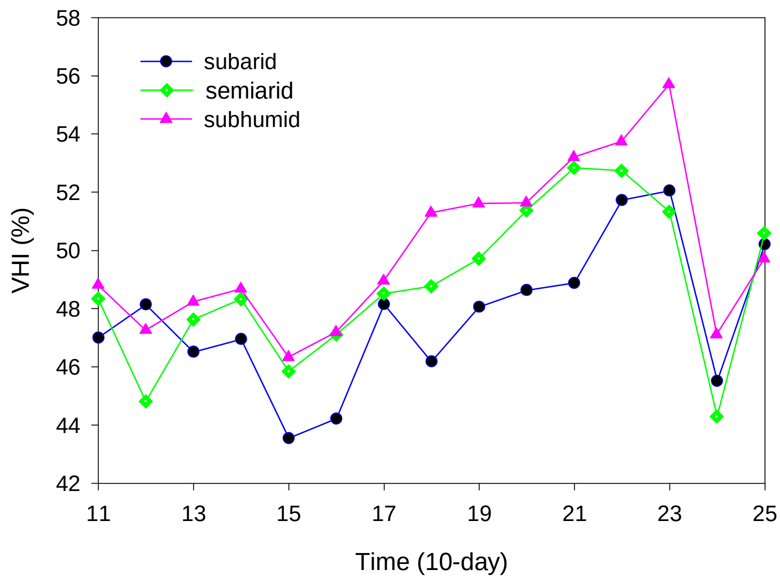

Figure 3: Five years time-series VHI temporal profiles in the agroclimatic regions

4.2 Wheat Yield Model

In order to determine the critical reproductive phase of wheat to calculate integrals of NDVI and VHI, a correlation analysis was carried out between wheat yield and the seasonal NDVI. Figure 4 illustrates how the coefficient of correlation varied from the beginning to the end of wheat growing season. The relationship between seasonal NDVI and wheat yield peak around 10-day period 20 (almost late July) for all agroclimatic regions after which the correlation coefficient decline rapidly as wheat crop begin to senesce. Overall, the correlation coefficient is relatively small except between 10-day periods 17 and 22 where almost 40% to 60% of the variability in yield is explained by the NDVI for subarid and semiarid regions, compared to 20% to 41% for subhumid regions. The higher correlation coefficient values are associated with the critical reproductive phase of wheat corresponding to the heading and grain production period that usually occurs during July. This maximum wheat vegetative period was then selected to calculate the integrals of NDVI (iNDVI) and VHI (iVHI) in order to develop wheat yield assessment models. Figures 5 and 6 show the variation of the correlation coefficient between wheat and both vegetation indexes over the integration period (from 10-day periods 17 to 22, expressed as 17-22X). As depicted, the correlation gradually increases to a maximum as the integration time increases then followed by a subsequent decreasing phase. The best iNDVI estimator reached a correlation peak at the integration time corresponding to 17-22X for subarid regions (R^2 = 0.59), almost late July to early August. For semiarid and subhumid areas, the peak correlation occurred at the integration time 17-21X and 17-22X for R^2 values of 0.57 and 0.44, respectively.

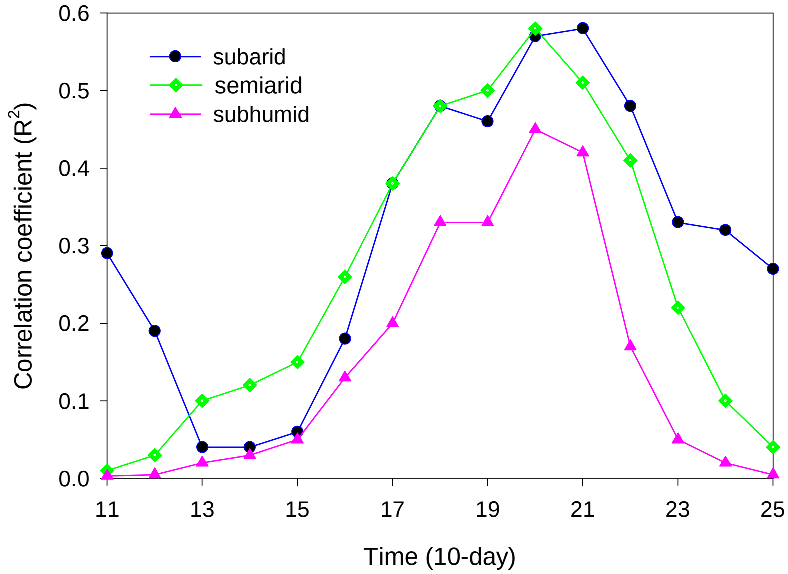

Figure 4: Correlation coefficient between NDVI and normalized wheat yield

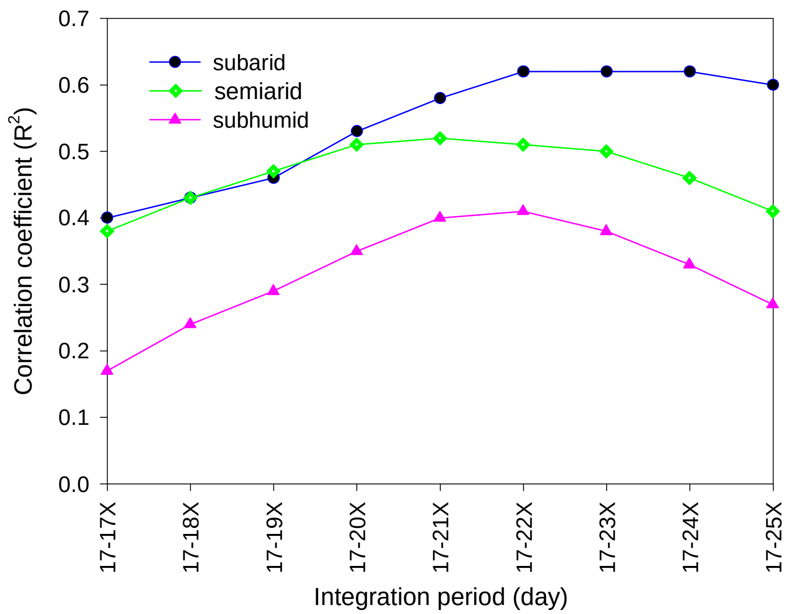

Figure 5: Correlation coefficient between integrated NDVI (iNDVI) and normalized wheat yield

The strength of the correlation between wheat yield and iVHI was also investigated in order to determine the response of wheat crop to moisture and thermal conditions as expressed by the vegetation health index. The correlation of yield versus iVHI showed a different dynamic compared to iNDVI (Figure 6). The correlation reached a peak at integration period 17-20X (late July) for semiarid and subhumid regions, while in subarid regions, the peak correlation is reached at 17-22X (early August) almost twenty days later in the season (Figure 6). This delay in wheat growing conditions may be related to rainfall deficit coupled with cool temperatures. The best iVHI-based model was obtained in the drought-affected subarid regions where three-quarters of the variation in wheat yield (R^2 = 0.75) is explained by the model; iVHI peaks correlation values of 0.61 and 0.34 were reached for semiarid and subhumid regions, respectively. However, both iNDVI and iVHI reached their lowest correlation coefficients in subhumid regions mainly due to the amount of water accumulated in the field due to frequent rainfall events. Indeed, the excess water affects reflectance values of NOAA/AVHRR channels 1 and 2 and causes a decrease in vegetation indexes as observed by Domenikiotis *et al.* (2004). Therefore, there is an increased of cloud contamination and water vapour content in the atmosphere, and those changes induced a decrease in both vegetation indexes, which affects their correlation with wheat yields. The higher correlation of iVHI in subarid regions indicates that this index is more sensitive to dry climate conditions and therefore suitable for estimating wheat yield in drought conditions. The results of wheat yield assessment based on the relationships with both vegetation indexes are presented in Tables 2 and 3. As shown in these tables, the best standard errors of the estimate yield are observed with iVHI-based models, particularly for the subarid and semiarid regions. In terms of MAE, iVHI-based model gave values of 2.2 bu/ac and 4.7 bu/ac for subarid and semiarid regions, respectively, while in subhumid regions, the lower value of MAE was found with iNDVI model (7.5 bu/ac). Overall, the high correlation coefficients observed in subarid and semiarid regions show that for the drought-affected areas on the Canadian prairies, wheat yield variability is largely explained by the time-integrated VHI. Therefore iVHI can be used to adequately forecast wheat yield loss due to agricultural drought on the Canadian prairies and indirectly estimates the drought severity. In regions with sufficient rainfall events, such as the subhumid regions, the iVHI plays a minor role in the estimation of wheat yield. The iNDVI reacts in the same way in these regions, but it performs better than the iVHI.

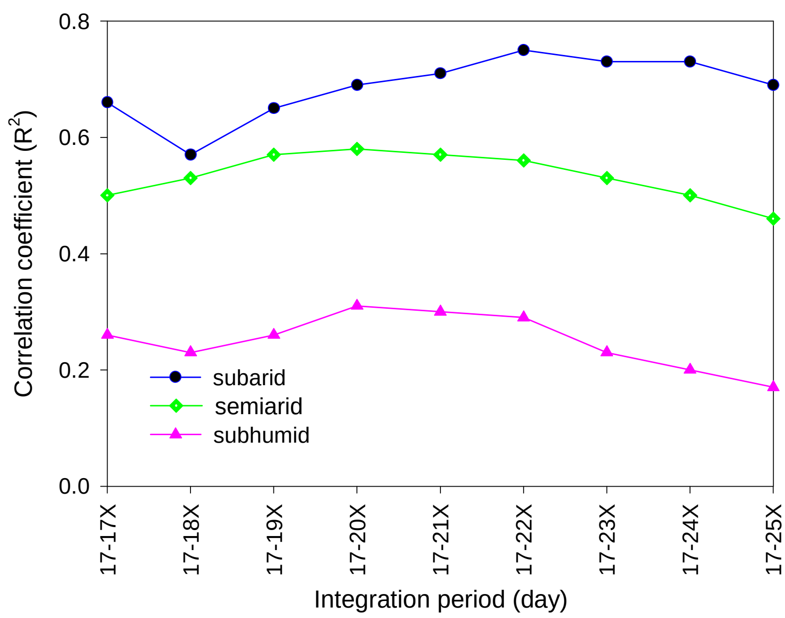

Figure 6: Correlation coefficient between integrated VHI (iVHI) and normalized wheat yield

Table 2. iNDVI-based wheat yield assessment model coefficients

Agroclimatic regions	*a*	*b*	R^2	Integration period
Subarid	3.16	0.72	0.59	17-22X
Semiarid	-8.73	0.90	0.57	17-21X
Subhumid	-28.48	1.31	0.44	17-22X

**Model parameters are significantly different from zero at 95% level.*

Table 3. iVHI-based wheat yield assessment model coefficients

Agroclimatic regions	*a*	*b*	R^2	Integration period
Subarid	12.03	0.27	0.75	17-22X
Semiarid	14.52	0.28	0.61	17-20X
Subhumid	20.44	0.31	0.34	17-20X

**Model parameters are significantly different from zero at 95% level*

Table 4. Estimated and observed wheat yields using the best linear models per agroclimatic region

Year	iVHI-based (Subarid)				iVHI-based (Semiarid)				iNDVI-based (Subhumid)			
	CAR	Obs.	Pred.	Resid.	CAR	Obs.	Pred.	Resid.	CAR	Obs.	Pred.	Resid.
2001	S3AS	23.20	24.78	-1.58	S02A	22.60	28.86	-6.26	M011	21.90	36.57	-14.67
2001	A001	16.90	17.35	-0.45	A04A	32.70	32.49	0.21	S09A	27.90	33.46	-5.56
2002	S3AS	24.48	25.88	-1.40	S02A	22.82	27.45	-4.63	M011	34.25	40.40	-6.15
2002	A001	27.13	24.30	2.84	A04A	10.86	16.31	-5.44	S09A	9.72	20.15	-10.43
2003	S3AS	19.06	15.37	3.68	S02A	16.32	19.09	-2.78	M011	46.35	38.19	8.15
2003	A001	25.27	23.07	2.21	A04A	33.29	32.30	0.99	S09A	28.07	27.49	0.58
2004	S3AS	28.64	28.00	0.64	S02A	25.04	28.14	-3.10	M011	45.85	33.95	11.90
2004	A001	30.66	28.53	2.13	A04A	43.41	32.82	10.59	S09A	34.14	31.08	3.06
2005	S3AS	28.80	33.58	-4.78	S02A	28.60	39.64	-11.04	M011	19.20	31.71	-12.51
2005	A001	37.30	34.80	2.50	A04A	41.60	39.90	1.70	S09A	40.20	41.70	-1.50
MAE = 2.2 bu/ac					MAE = 4.7 bu/ac				MAE = 7.5 bu/ac			

5. Conclusion

The performance of NOAA/AVHRR indexes for wheat yield assessment on the Canadian prairies was evaluated. We focused on the relation of time-series of two integral vegetation indexes (iNDVI and iVHI) with wheat yield dataset. The aim was to compare the performance of both indexes toward an operational implementation of a wheat yield assessment system. We used the Mean Absolute Error (MAE) and the correlation coefficient in order to evaluate the assessment performance of wheat yield models based on these indexes. Results showed that that although NDVI temporal pattern is consistent with wheat yield variations in agroclimatic regions, it does not highlight the punctual unfavourable growing conditions occurring during the season. Contrary to NDVI which mainly reflects wheat crop greenness, VHI shows weather-related fluctuations impacting on the crop conditions. In terms of wheat yield assessment under drought conditions, iVHI demonstrated higher potential when compared to iNDVI in subarid and semiarid regions. iNDVI gave better results in estimating wheat yield in subhumid Prairies regions characterized by frequent rainfall events. Consequently, to develop an efficient wheat yield assessment model for the entire Canadian prairies on an operational basis, the iVCI and iNDVI should be coupled in the same model to better account for all agroclimatic regions characteristics. This combined model will significantly improve wheat yield assessment on the Prairies leading to better wheat marketing strategies and assessing population demand.

Despite the promising results found in this study further investigations need to be carried out to improve its predictive performance. The best wheat yield estimates are reached at an integration period corresponding to almost six weeks before the harvest, which is too late to take corrective actions particularly in Canadian prairies where drought occur frequently. In addition, further work will be undertaken to include in the yield model other meteorological parameters that have control on the drought conditions. Finally, the wheat yield model should be extent to the MODIS (Moderate Resolution Imaging Spectroradiometer) dataset to take advantage of its intermediate 250-m spatial resolution and its flexibility in image compositing periods**.**

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