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Relationship between MODIS-NDVI data and wheat yield: A case study in Northern Buenos Aires province, Argentina

Mariano F. Lopresti [a,*], *Carlos M. Di Bella* [b,d], *Américo J. Degioanni* [c]

[a] *Instituto Nacional de Tecnología Agropecuaria (INTA), EEA Pergamino, Ruta 32 km 4.5, Pergamino 2700, Buenos Aires, Argentina*
[b] *INTA-Castelar, CNIA, Instituto de Clima y Agua, Las Cabañas y Los Reseros S/N, Hurlingham 1686, Buenos Aires, Argentina*
[c] *UNRC, Facultad de Agronomía y Veterinaria, Departamento de Ecología Agraria, Ruta Nacional 36 km 601, Río Cuarto 5800, Córdoba, Argentina*
[d] *CONICET – Consejo Nacional de Investigaciones Científicas y Técnicas, Argentina*

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A B S T R A C T

In countries like Argentina, whose economy depends heavily on crop production, the estimation of harvests is an elementary requirement. Besides providing objectivity, the use of remote sensing allows estimating yield in advance. Since the time of maximum leaf area in wheat corresponds with the critical period of the crop, a good relationship is expected between the Normalized Difference Vegetation Index (NDVI) and yield. The present study was carried out in the North of Buenos Aires province, Argentina. Based on the type of soil, the study area can be divided into two homogeneous subzones: a subzone with lower clay content in the southwest and a subzone with higher clay content in the northeast. Nine growing seasons (2003–2011) were studied. In the first five years, an empirical model was calibrated and validated with field-observed wheat yields and MOD13q1 product-NDVI data, whereas in the other four years, the calibrated model was applied by means of yield maps and by comparing with official yields. The MOD13q1 image corresponding to Julian day 289 showed the best fit between NDVI and yield to estimate wheat yield early. Through yield maps, better weather conditions showed higher yields and higher soil productivity presented a greater proportion of the area occupied by higher yields. At department level, an R^2 value of 0.75 was found after relating the estimation of the calibrated empirical model with official yields. The method used allows predicting wheat yield 30 days before harvest. Through yield maps, the NDVI perceived the temporal and spatial variability in the study area.

1. Introduction

In countries like Argentina, whose economy depends heavily on crop production, early harvest estimations are an elementary requirement to generate national budget, plan public strategies due to natural disasters and anticipate the demand for transport and storage. In Argentina, wheat (*Triticum*

* Corresponding author. Tel.: + 54 2477 439038/48.
E-mail address: lopresti.mariano@inta.gob.ar (M.F. Lopresti).

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aestivum L.) is an important crop (the total production of the 2011 season was 14,500,517 tn [1]), mainly concentrated in the Humid Pampa Region, where Buenos Aires is the most important province, with around 60% of the country's production. Argentine official estimates of yield are currently made mainly through interviews with qualified informants. Taking into account the subjectivity and low representativeness of this technique, agricultural estimates through remote sensors are increasingly being considered worldwide [2–8].

Remote sensors allow estimations in an advance way and with lower cost than traditional techniques [9]. Besides its objectivity, the observation by remote sensing provides homogeneous data which can be geographically and temporally recorded [10]. However, the use of remote sensing is not as effective to estimate crop yield as to estimate the occupied area [11,12], where the observation is more direct and where finding a method applicable to different crops, areas and growing seasons is more viable. [13] concluded that estimating yield by Normalized Difference Vegetation Index (NDVI), obtained in an early, fast and inexpensive way, could be considered as a promising complement to the survey-based yield assessments (currently applied by the Ministry of Agriculture in Morocco). In India, the efficiency of crop yield estimation has been found to improve substantially after combining satellite spectral data with survey data based on crop cutting experiments [14].

NDVI, closely related to the vegetation vigor [15], has been recognized for its ability to monitor crops and as an estimator of crop yields since early 1980s [16–21]. NDVI has an asymptotic non-linear relationship with the green Leaf Area Index (LAI) of some crops [22–24]. A variation in LAI implies different intercepted radiation that, according to the Radiation Use Efficiency (RUE), is directly related to the production of biomass that will determine the possible yield [25]. As the critical period of wheat (20 days before to 10 days after flowering) corresponds with the time of maximum leaf area [26], a good relationship between NDVI and yield is expected. Wheat yield predictions have been possible using data from a single image at the peak of crop development, which encompasses the critical period for grain production [14,27,28].

Therefore, it is possible to predict the wheat yield of a certain region by empirical models that relate the NDVI at the maximum leaf area moment with yield. A main drawback of empirical models that estimate yield from spectral data is that their application is limited to regions for which they were calibrated [29–31]. However, these empirical models are often preferred because they require fewer data and are simple to implement at regional scale [28]. [13] used NDVI and weather data to estimate wheat yield, and found that the NDVI appeared to contain most of the information on rainfall and explained most of the grain yield variability. Many researchers have coupled remote sensing data with crop models [30,32,33] or agrometeorological models [34,35] to estimate crop yield at regional scale. Although crop growth simulation models are more accurate to estimate yield, they require numerous specific inputs (not always available) such as soil characteristics, management practices, agrometeorological data and crop parameters. As stated by [33], the great variations in crop varieties at the regional scale and in different years make it difficult to regionalize crop parameters.

The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor has a spatial and temporal resolution that allows monitoring and mapping the vegetation at regional level. With minimal variations associated with external influences (atmosphere, view and sun angles), MODIS vegetation index products provide consistent spatial and temporal comparisons of vegetation conditions [22]. Although these types of images do not have high spatial resolution, it is possible to have cloud-free images because of the high revisit frequency of the sensor (1–2 days). Higher spatial resolution satellites are usually only available a few times a year for a given location. This is due to the lower revisit frequency and cloud cover frequency [27,31]. MODIS products have no cost and are available to the user community in the web. By means of empirical models, several studies have recently related MODIS data and crop yield at regional scale [28,31,36–38].

As the Argentine Humid Pampa has large wheat production plots and the phenological stages are similar within an area, the objectives of this study were: (i) to fit an early method of estimation of wheat yield in Northern Buenos Aires from MODIS-NDVI and, therefore (ii) to generate a regional cartography of wheat yield prior to harvest. The results could provide an inexpensive and early estimation of wheat yield and the possibility to identify areas with different levels of production.

2. Materials and methods

2.1. Study site

The study area is located in the North of Buenos Aires province (33–34°S and 59–60°W) in the Argentine Humid Pampa (Fig. 1). The area covers 1,603,747 ha, including 12 departments, and is predominantly an agricultural region dominated by soybean (Glycine max L. Merr.), maize (Zea mays L.) and wheat as main crops. The relief is characterized by smooth slopes (0–2.5%) and long length (400–800 m) [39]. The climate is humid temperate with a monsoon-type rainfall pattern (Fig. 2). The average annual rainfall is 1030 mm and the annual mean temperature is 17 °C. The soil type is Argiudoll with a gradual increase in clay content to the northeast of the region. According to the division in Agroecological Zones of INTA-RIAN (http://rian.inta.gov.ar/consultaagronomica/(S(y2lwt0eq4lcx4x51umky3kt1))/default.aspx), the study area can be divided into two more homogeneous subzones (Fig. 1): Subzone VI-I, in the southwest, with lower clay content in soil, presents Typic Argiudolls and Subzone VI-J, in the northeast, with higher clay content in soil, presents Vertic Argiudolls. According to [40], Typic Argiudolls present higher soil Productivity Index (PI) [41] than Vertic Argiudolls, therefore, the Subzone VI-I, in the southwest, presents higher soil PI than the Subzone VI-J, in the northeast. Fig. 3 shows that the rainfall and mean temperature from INTA EEA Pergamino and San Pedro meteorological stations are similar, the largest difference is presented for the rainfall of June (14 mm).

2.2. Crop

Wheat in the Argentine Humid Pampa is produced under rainfed conditions and no-tillage system is used. Within the crop

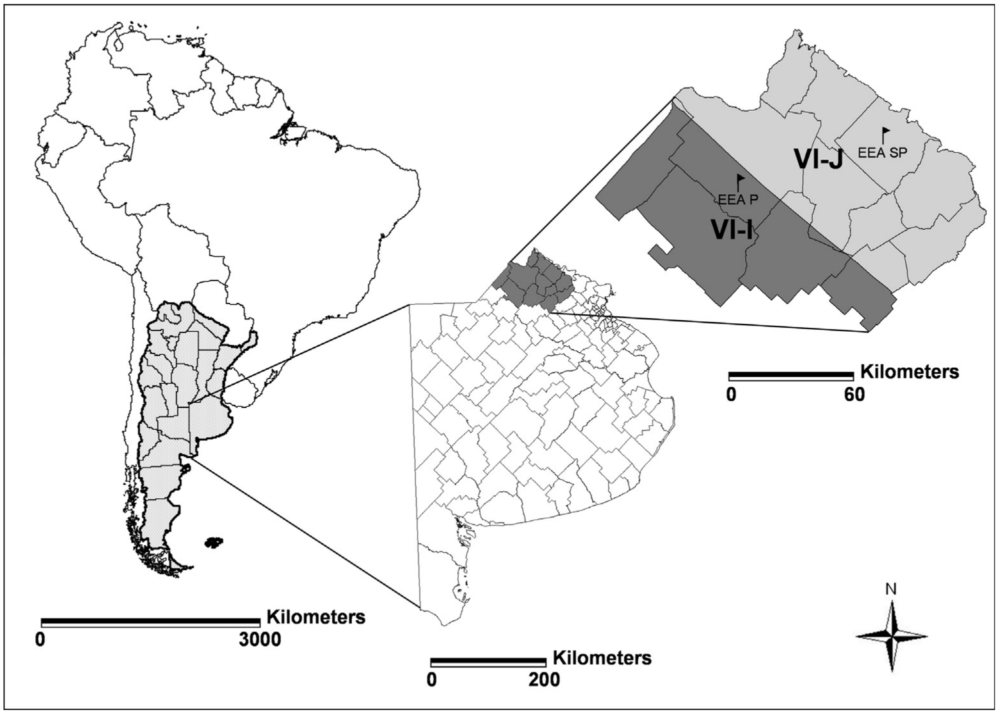

Fig. 1 – Location of the study area in Buenos Aires Province, Argentina. VI-I and VI-J: homogeneous Subzones (INTA-RIAN); EEA P and EEA SP: INTA EEAs Pergamino and San Pedro.

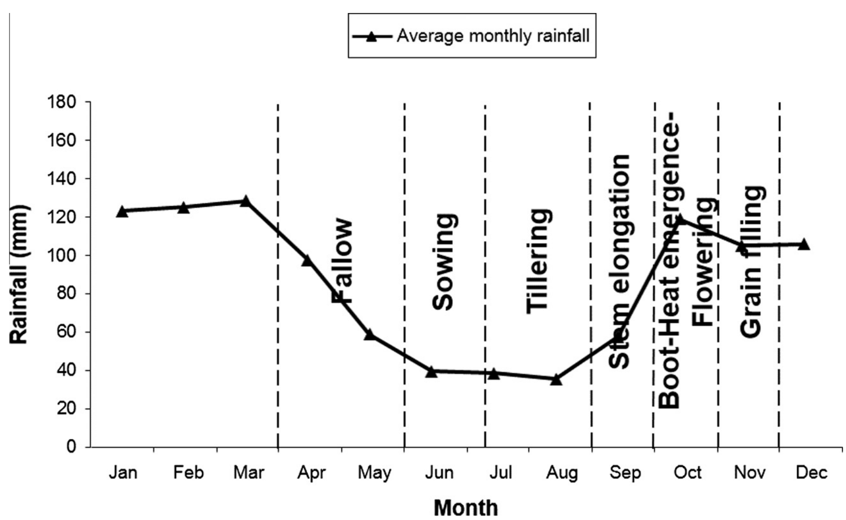

Fig. 2 – Rainfall pattern and wheat phenological stage. Data source: Averages values from INTA EEA Pergamino and San Pedro meteorological stations (historical climate data from 1970 to 2011) and INTA-RIAN (Crop monthly monitoring).

rotation, the wheat is cultivated in the wheat-soybean double cropped sequence and the previous crop is full-season soybean. Sowing in Northern Buenos Aires is in June and the first decade of July. Fig. 2 shows the phenological stages of the normal growth cycle of wheat in the study area. The critical stage for water availability occurs during October, and the grains number m^{-2}, which is the main yield component, is defined toward the end of this month. Grains weight is defined in November, and physiological maturity occurs before December. The duration of grain filling is influenced mainly by temperature: a rise of 15 °C, from 10–15 °C to 25–30 °C, reduced the duration of grain growth by about two-thirds [42]. During October and November (critical period and grain filling), wheat yield is very sensitive to frosts. The average date of the last frost at 1.5 meters in the study area is before September 15. Harvest is in late November–early December.

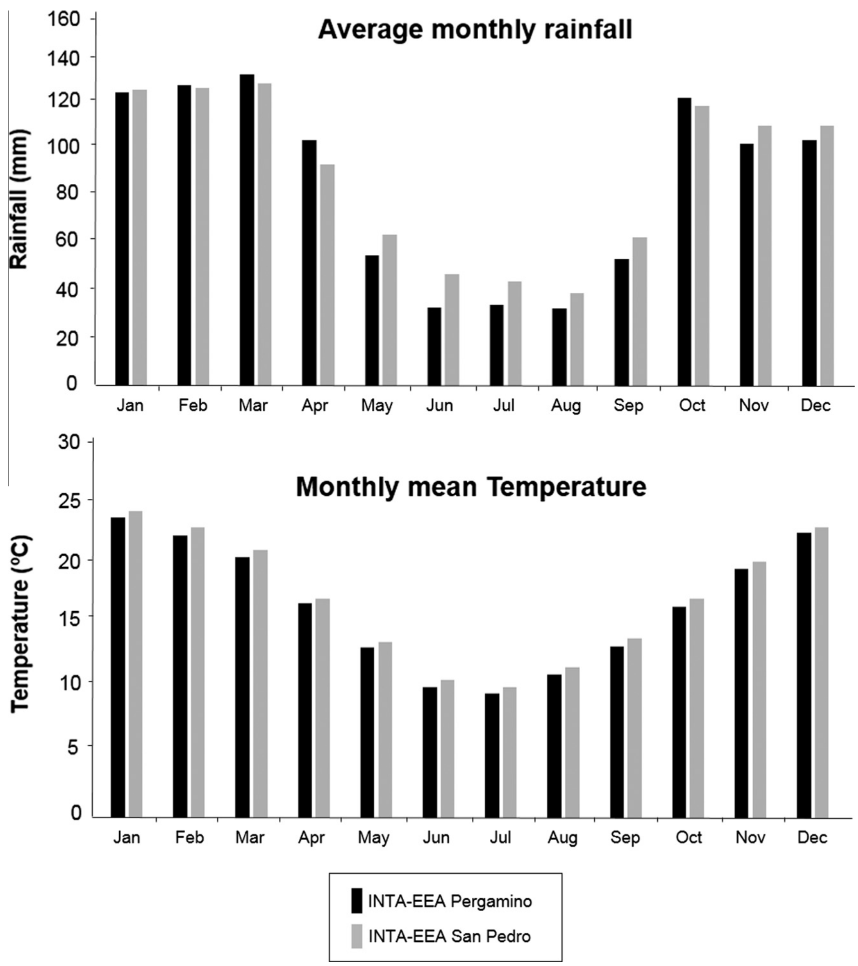

Fig. 3 – Monthly rainfall and monthly mean temperature from INTA EEA Pergamino and San Pedro meteorological stations (historical climate data from 1970 to 2011).

2.3. *Agrometeorological description of the period 2003–2011*

The 2008 season was the driest, being notably different from the others in total rainfall (Table 1). The 2003, 2004 and 2005 seasons presented the least amount of rainfall in September–October (stem elongation and critical period), which is the moment of highest crop water demand. Studies in Argiudoll soils in the South of Santa Fe (near the North of Buenos Aires) have shown that the wheat water consumption in the region is 400–450 mm [43]. Therefore, the 2007 and 2008 seasons did not have enough total rainfall, but the 2007 season presented more rainfall in September–October. The 2004, 2006 and 2010 seasons

Table 1 – Weather conditions of the period 2003–2011.

Growing season	Rainfall-April–November (mm)*	Rainfall-September–October (mm)	Thermal sum-November (°Cd)**
2003	502	76	609
2004	436	68	589
2005	416	102	641
2006	452	223	592
2007	367	214	566
2008	252	124	717
2009	603	178	614
2010	428	168	587
2011	400	123	647

Data source: Averages values from INTA EEA Pergamino and San Pedro meteorological stations.
* Total rainfall for wheat (the previous crop, full-season soybean, is harvested at the beginning of April).
** Thermal sum = Σ(mean daily temperature − base temperature). Base temperature: 0 °C.

presented similar thermal sum during November (around 590°Cd) when grain filling occurs. During October and November (critical period and grain filling) no frosts were recorded at 1.5 m in any of the seasons studied (INTA-EEA Pergamino and EEA San Pedro).

2.4. *Field surveys and MODIS-NDVI data*

Data on field-observed wheat yields of five growing seasons (2003–2007) were collected in 2008 by means of interviews with farmers that record their production. A total of 125 yield data were obtained. The surface of sampled plots varied between 20 and 141 ha. These samples were used to calibrate an empirical model of yield with spectral information. The MODIS product used in this study was MOD13q1, which is a 16-day maximum value composite (MVC) with a 250-m spatial resolution. NDVI data of MOD13q1 Collection five were obtained from http://e4ftl01.cr.usgs.gov/MOLT/MOD13Q1.005.

In order to cover the period of greatest LAI of the crop, five MVC were acquired for each growing season (Table 2). Therefore, the relationship between NDVI and wheat yield was observed from September 14 to December 2.

2.5. *Calibration and validation: image processing and data analysis*

Two MOD13q1 scenes (h12-v12 and h13-v13) were necessary to cover the study area. So, a mosaic was done for each date studied (257, 273, 289, 305 and 321). For each growing season (2003–2007), a layer stack was made with the MOD13q1-NDVI of each date. The layer stacks were used to extract the NDVI information of wheat samples for each date studied. Each layer stack were linked to a Landsat image of the same year to select MODIS pixels. The Landsat images, with a 30-m spatial resolution, allowed to identify the MODIS pixels of wheat plots. Following [23] and [44], the average of NDVI values per wheat plot was calculated. This was considered the best way to represent the intercepted radiation within the plot when the value of yield is only one. Images were processed with [45].

Once the NDVI information was joined with yield data, approximately 75% of samples were used to calibrate the empirical model and 25% (randomly separated) to validate it. An intra-annual and inter-annual analysis was made to choose the best yield model and observe the influence of agrometeorological conditions. The relationship between NDVI and wheat yield was observed through the linear regression model, where the dependent variable was represented by wheat yield and the independent variable by NDVI. Several studies have used the linear regression model to describe the relationship between NDVI and wheat yield in different regions [13,28,36,44]. The statistical significance in all analyses was determined by a p-value <0.05, and the statistical software used was [46].

2.6. *Application: image processing and data analysis*

During the 2008–2011 period, the calibrated empirical model was applied by means of yield maps and the estimated average wheat yield of each department was compared with official yields of the Ministry of Agriculture, Livestock and Fisheries in Argentina (Ministerio de Agricultura, Ganadería y Pesca, MAGyP).

Since the 2008 season, it is possible to have a winter crops map for the study area (INTA EEA Pergamino-GIS Group). This map, besides wheat, includes barley and oat, but as these crops are not important in the study area, the wheat area was considered as the area of winter crops. Therefore, prior to the yield estimation, a mask with the crop area was applied on the MODIS image. Applying a cropland mask to select NDVI values as input to a crop yield model significantly improves the accuracy of the crop yield estimation [19,28,36,47,48]. The calibrated yield regression model was applied on the wheat NDVI image. In the yield image generated, we considered only the subset of yields above 2500 kg ha^{-1} for the 2009–2011 seasons and above 1000 kg ha^{-1} for the 2008 dry season (the minimum and maximum between the average official wheat yields for each department for the 2009–2011 seasons were 4183 and 5396 kg ha^{-1} whereas those for the 2008 season were 1700 and 3000 kg ha^{-1} [1]). In order to generate the yield map, the yield image was classified in five classes or yield categories (<3200, 3200–3700, 3700–4200, 4200–4700 and >4700 kg ha^{-1}) and a majority filter with a window size of 3×3 was applied to obtain a clearer spatial distribution of categories and attenuate large contrasts in contiguous pixels. Using filters was an effective tool to estimate crop yield from MODIS data [31,36]. Finally, the yield map was used as a mask on the yield image to obtain the average wheat yield for each department and for each homogeneous subzone.

The proportion of area occupied by the map yield categories was calculated for each growing season (2008–2011) in the homogeneous subzones and the average yields of each homogeneous subzone were compared within the study area.

Table 2 – Acquired dates of the MOD13q1 product (2003–2007).

Date (Julian day)*	16-day MVC**
257	September 14–29
273	September 30–October 15
289	October 16–31
305	November 1–16
321	November 17–December 2

* First Julian day of the 16-day composite.
** Periods correspond to 2003, 2005, 2006 and 2007. For 2004 (leap year), the period must be advanced one day.

3. Results and discussion

3.1. Relationship between NDVI and wheat yield

3.1.1. Intra-annual analysis

After observing the linear relationship between field yields and the five MOD13q1 dates studied (Table 3), dates 289 and 305 (October 16–31 and November 1–16) showed the highest fit between NDVI and yield (*p*-value: 0.0003). Furthermore, the relationship between NDVI and yield presented by simple regression models on dates 289 and 305 (Table 4) showed a similar explanation of the yield total variation (R^2 values). Therefore, since the models of dates 289 and 305 predict the yield in the same way, the anticipation of 16 days led us to select date 289 (Eq. (1)) to estimate the wheat yield in Northern Buenos Aires. In consequence, using the MOD13q1 image of Julian day 289, it is possible to estimate wheat yield 30 days before harvest. The wheat production in Ukraine was predicted six weeks prior to harvest using an empirical remotely sensed-based yield model [28]. During the second half of October, the wheat in Northern Buenos Aires is in the phenological stages of head emergence and anthesis (within the critical period). [36] found similar results in Shandong, China: they obtained a good prediction of wheat yield during booting and heading stages using MODIS-NDVI data. The best correlation between NDVI and wheat yield coincided with the period of highest LAI. The maximum leaf area of wheat is achieved 10–15 days before anthesis [49]. [50] have found good relationships between wheat yield and NDVI during the later part of the growing season, prior to harvest, at the regional scale.

$$\text{Wheat yield } (\text{kg ha}^{-1}) = -4630.51 + 10991.94(\text{MOD13q1\_289\_NDVI}) \quad (1)$$

Table 3 – ANOVA table for multiple regression between yield and MOD13q1-NDVI dates analyzed.

Source	SS	df	MS	F	*p*-value
Model	43342589	5	8668518	25.70	<0.0001
ndvi_257	317035.9	1	317035.9	0.94	0.3351
ndvi_273	1232170.5	1	1232171	3.65	0.0594
ndvi_289	4871548.2	1	4871548	14.44	0.0003
ndvi_305	4874943.2	1	4874943	14.45	0.0003
ndvi_321	1899171.8	1	1899172	5.63	0.0199
Error	28334518.5	84	337315.7		
Total	71677108.2	89			

Table 4 – Simple regression between yield and MOD13q1-NDVI dates analyzed.

MOD13q1 date	R^2	*n*	*p*-value NDVI
257	0.13	90	0.0004
273	0.16	90	0.0001
289	0.52	90	<0.0001
305	0.51	90	<0.0001
321	0.17	90	<0.0001

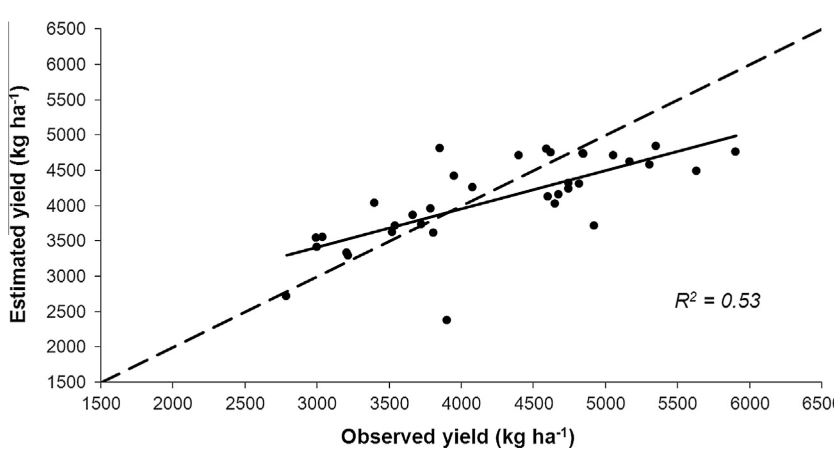

Fig. 4 – Relationship between observed and estimated yield using the calibrated model with the MOD13q1-NDVI of the date 289. *n* = 35, *p*-value = <0.0001, root mean squared error (RMSE) = 582 kg ha^{-1}.

Table 5 – Linear relationship between MOD13q1-289-NDVI and wheat yield in the 2003–2007 growing seasons.

Growing season	Calibration			Validation			
	R^2	n	p-value	R^2	n	p-value	RMSE (kg ha^{-1})
2003	0.59	13	0.0023	0.08	5	0.6545	–
2004	0.57	13	0.0028	0.69	7	0.0201	405
2005	0.33	16	0.02	0.11	7	0.4774	–
2006	0.75	22	<0.0001	0.65	9	0.0086	400
2007	0.23	26	0.0142	0.18	7	0.3480	–

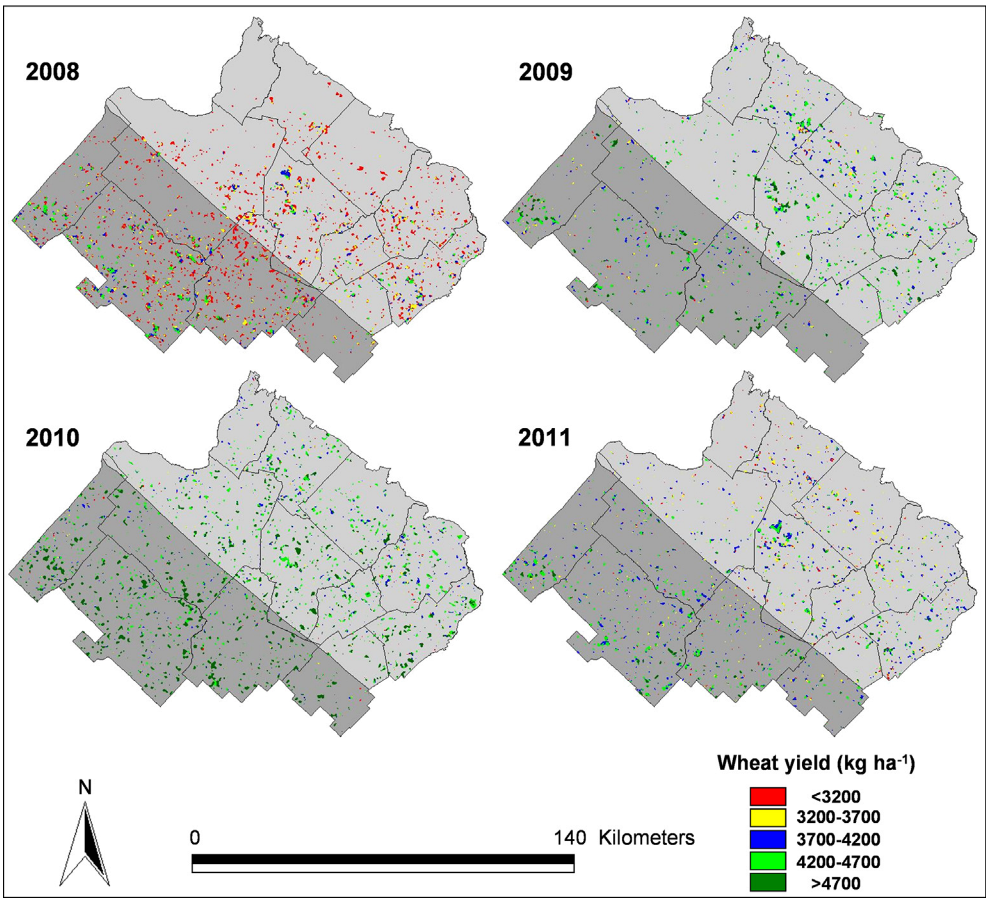

Fig. 5 – Yield estimation by the calibrated model with the MOD13q1-289-NDVI image for the 2008–2011 growing seasons.

The calibrated yield prediction model was validated (Fig. 4), the RMSE value (582 kg ha^{-1}) represents a 14% of the average of observed yields, which shows an acceptable degree of dispersion between observed and estimated values. Similar results (RMSE: 440 kg ha^{-1}, error: 15%) were found to predict wheat yield in Ukraine [28]. [31] estimated the regional wheat yield from MODIS data with a RMSE of 570 kg ha^{-1}, representing about 7% of the mean of observed yields. [51], after combining a crop growth model and remotely sensed data, estimated the regional wheat yield with a RMSE value of 775 kg ha^{-1} and a R^2 of 0.51. The dispersion between observed and estimated yields can be attributed to two main reasons. First, in contrast to forage crops where yield corresponds to the vegetative parts and its observation by remote sensing is direct, in crops like wheat, whose yield consists of storage organs, the observation is indirect. Unlike crops whose yield consists of total above-ground production, wheat yield is contained in storage organs and is very sensitive to meteorological conditions at critical growth stages. This means that although above-ground biomass may be high, grain yield may not be commensurately large [29]. In addition, after using MOD13q1-NDVI (date 289) to estimate wheat yield, there is still one month before harvest. Weather conditions and biotic adversities during November (grain filling) influence yield and thus the inference of NDVI from October 16–31 can change. [28] found that high values of NDVI in the peak of wheat growth were related to low yields due to a meteorological event prior to harvest, a late frost caused low yields despite the high green biomass that had been established.

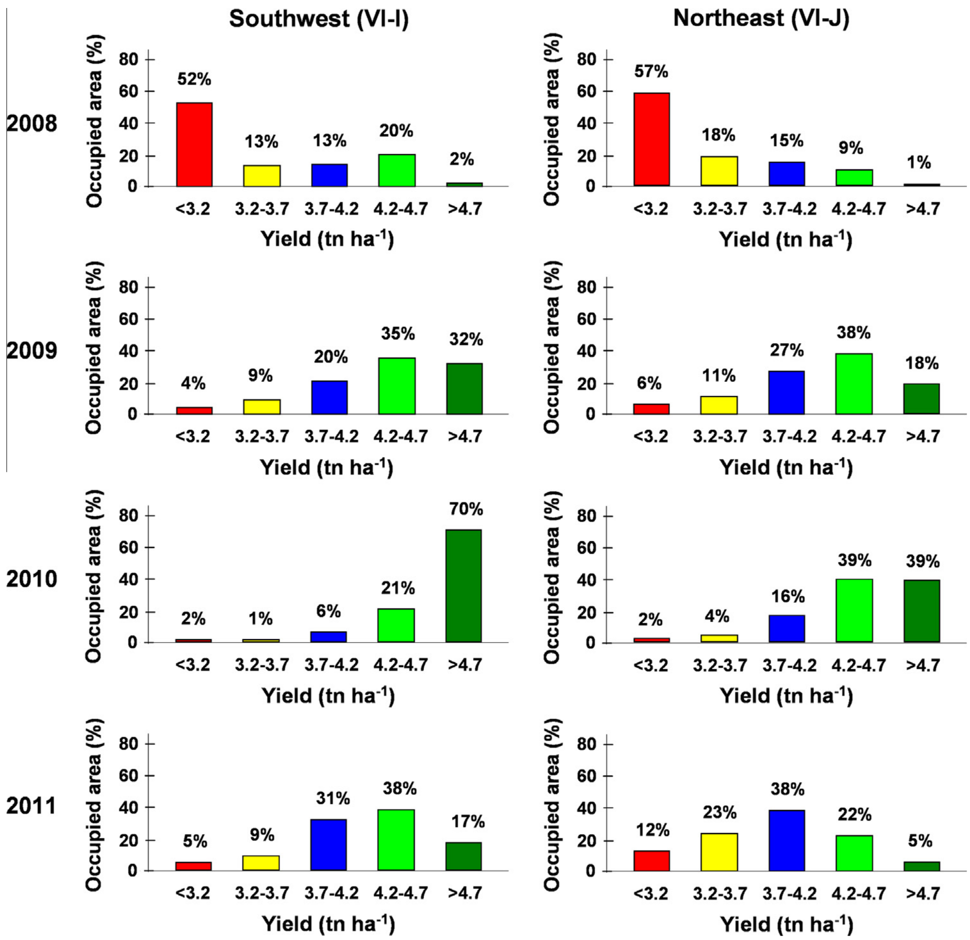

Fig. 6 – Proportion of occupied area for each yield category in the homogeneous subzones within the study area.

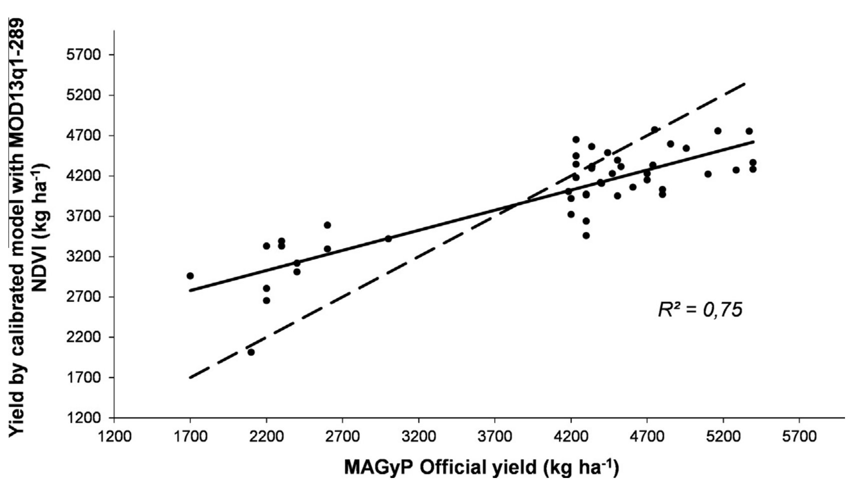

Fig. 7 – Relationship between estimation of calibrated empirical model and MAGyP official yields for the average wheat yield for each department in four growing seasons (2008–2011). Number of Departments: 12.

3.1.2. *Inter-annual analysis*

Table 5 shows that the relationship between MOD13q1–289-NDVI and yield was best described in the 2003, 2004 and 2006 growing seasons (R^2 values), and that only the models for the 2004 and 2006 seasons were validated (*p*-values). The inter-annual variation observed indicates the influence of agrometeorological conditions on yield estimation by NDVI. Although the relationship between NDVI and crop productivity depends largely on the phenological stage [36], also depends on the growth conditions. The 2004 and 2006 growing seasons (validated models) differed from each other in the amount of rainfall during September–October (68 versus

223 mm), but were similar in the thermal sum presented during November (around 590°Cd). [19] emphasized the incidence of grain filling period in the wheat yield spectral information-based estimation. [29] have mentioned calculating degree days in wheat growth stages as an important variable in yield estimation by remote sensing.

The relationship studied was significantly improved compared to the model found in the intra-annual analysis only in the model of the 2006 growing season ($R^2 = 0.52$ versus 0.75). The 2006 season presented good water availability for grain production in the critical period. So, under certain thermal conditions at the end of the growing cycle, better growth conditions during the critical period could improve the relationship between NDVI and yield. [52] constructed a model to predict wheat yield as a function of a vegetation condition index based on satellite data during the critical period of crop growth. [30] obtained high accuracy in wheat yield estimation at provincial level by using the NDVI to calculate the crop above-ground biomass and to adjust a harvest index depending on pre- and post-anthesis crop conditions. Therefore, if the spectral information is combined with agrometeorological data in a single model, more accuracy in yield estimation could be expected. However, the MOD13q1-289-NDVI allows obtaining great yield information early, and the accuracy will depend, among other things, on the weather conditions that will occur during grain filling.

3.2. *Yield maps*

Using a cropland mask, the calibrated model was applied on the study area for the 2008–2011 growing seasons (Fig. 5). Visually, there is a clear difference between the 2008 season

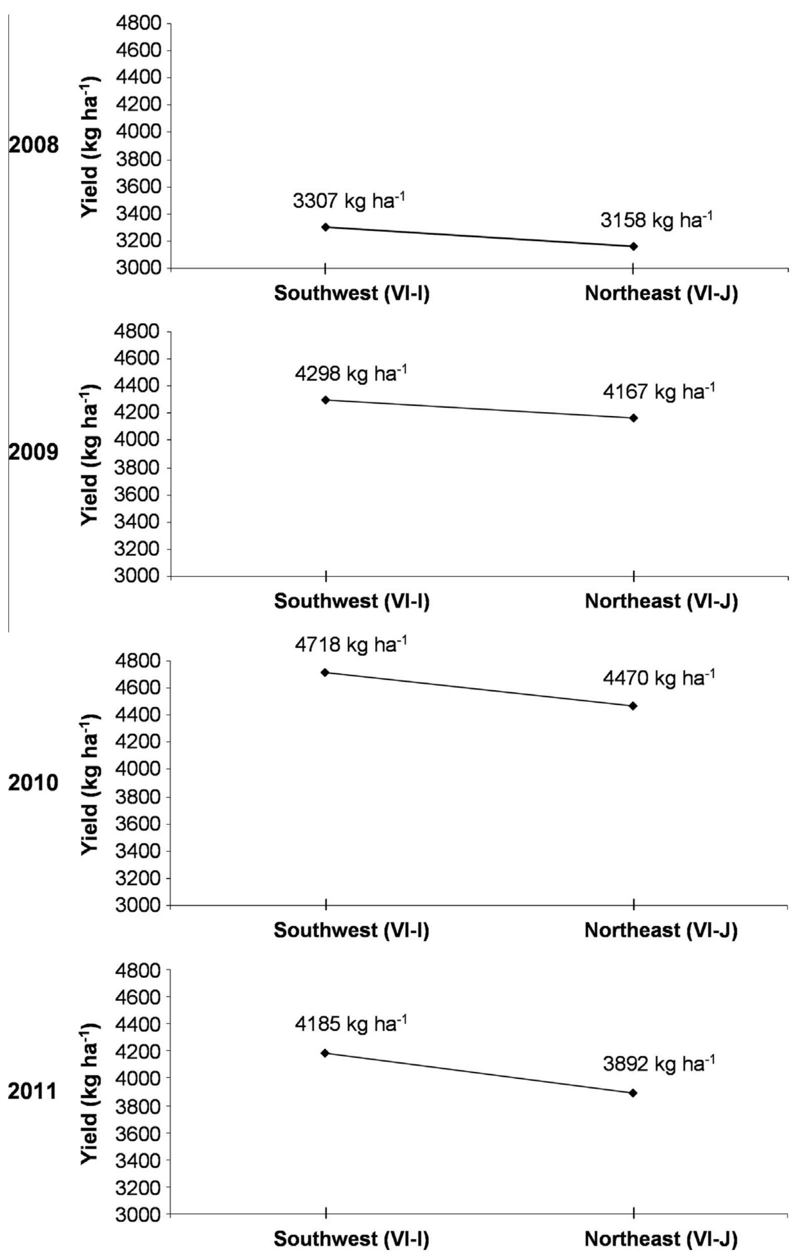

Fig. 8 – Average wheat yield for each homogeneous subzone.

and the other seasons, since the drought in the 2008 season was reflected in wheat yields. As previously reported, the weather conditions (closely linked to vegetation vigor) were related to the NDVI. The 2009, 2010 and 2011 seasons, with greater rainfall amount for wheat, showed higher yields. The calculation of the proportion of occupied area for each yield category in the homogeneous subzones within the study area (Fig. 6) showed that the southwest subzone (with higher soil PI) presented greater proportion of yields above 4.7 tn ha^{-1} and that the northeast subzone (with lower soil PI) showed greater proportion of yields below 4.2 tn ha^{-1} in the four growing seasons studied. If we consider the yields both below and above 4.2 tn ha^{-1}, the difference in the proportion of occupied area between the homogeneous subzones was 12%, 11%, 13% and 28% for the 2008, 2009, 2010 and 2011 seasons, respectively.

Therefore, by means of yield estimation, the NDVI perceived the temporal and spatial variability in the study area. Better agrometeorological conditions showed higher yields and a higher soil PI presented a greater proportion of the area occupied by higher yields. Maps of MODIS vegetation indices allow representing spatial and temporal variations of vegetation [22]. Classes of spatial variability of NDVI were correlated with maps of wheat accumulated biomass and grain productivity with a correspondence of 81% and 48%, respectively [53]. MODIS vegetation index images showed sensitivity to the variability of the vegetation among seasons and exhibited good association with winter crop yields [54]. The difference in production volumes (perceived by NDVI) between homogeneous subzones within the study area, inevitably, implies a different demand for grain transport and storage.

3.3. Comparison with official yields

The relationship found after comparing estimated yields for each department with official yields (Fig. 7) gives further validation to the calibrated model. In dry years, the model overestimates yield: the biomass can be green but the grain number and grain weight are lower. High yields are only attained with higher vegetation vigor, but the inverse is not always true: high biomass is not a guarantee of high yields and depends on the weather conditions at the reproductive phase, for example, water deficit in the critical period [54]. In wet years, the model underestimates yield: the index can become saturated and not read very high yields. With very high yields and very dense green biomass, the NDVI is likely to saturate prior to capturing the seasonal green biomass peak and therefore the study model peak NDVI would not serve as a good predictor of yield [28]. The inter-department yield variability was well perceived ($R^2 = 0.75$), and so the calibrated model was a good tool to predict the wheat yield at department level.

As observed in yield maps, the average wheat yield for each homogeneous subzone (Fig. 8) shows the temporal and spatial variation perceived through NDVI. The 2008 season, which was dry, presented lower yields than the other seasons in both subzones and, in all seasons, the southwest subzone (with higher PI) presented higher average yields than the northeast subzone (with lower PI). The difference in yield between the subzones studied for each season was 149, 131, 248 and 293 kg ha^{-1} for 2008, 2009, 2010 and 2011, respectively. However, it is important to highlight the relative or qualitative valuation of these results despite the quantitative differences. At present, the main contribution of remote sensing to the description of the crop condition is that it provides objective criteria of zonal and temporal comparisons. In addition, it provides information about geographic variability [55].

4. Conclusions

The method used in this study allows predicting wheat yield 30 days before harvest, after stages of heading and anthesis. Through the calibrated model, the NDVI perceived the temporal and spatial variability in the study area. It was possible to make objective comparisons between zones and growing seasons. The calibrated model was a good tool to predict the wheat yield at department level. The inter-annual variation, observed in the description of the relationship between NDVI and yield of the data analyzed, indicates the possibility of considering agrometeorological conditions to obtain accuracy in yield estimation. This requires more research, especially, in order to use the minimum number of inputs or available data. The model developed in this study should be tested in other wheat humid regions to confirm the results found in Northern Buenos Aires.

Acknowledgments

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