THE VALUE OF NOAA AVHRR INDICES FOR CORN YIELD ESTIMATES IN ARGENTINA

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ABSTRACT

Satellite data may contributed to improve the understanding of climate variations and the physical and biological relations of the environment. In this study the application of NOAA-AVHRR satellite data for predicting yield of corn in the main cropping area of Argentina was analyzed. The results have shown that VCI/TCI indices are effective indicators of the crops conditions and yield, providing greater and on time spatial and temporal coverage than the one is possible from ground-based measurements. Corn yield developed models based on VCI and TCI can provide reliable and timely yield estimates of regional agricultural production.

Key words: satellite monitoring, prediction, corn yield

INTRODUCTION

Satellites provide an alternative source of data to address some of the problems of ground-based assessments. The Advanced Very High Resolution Radiometer (AVHRR) sensor of the National Oceanic and Atmospheric Administration (NOAA) satellites allows applications at regional and global scales that require temporal coverage and global perspective. Primary production estimates, vegetation conditions, droughts monitoring from NOAA-AVHRR derived imagery can produce usefull information that has not been previously available. One of the products is the Normalized Vegetation Condition Index (NDVI), which has been successfully used for many authors (Kidwell, 1994; Los et al., 1994; Gutman et al., 1995; Goward et al., 1994; Maiden et al., 1994; Kogan, 1994b). Rasmussen (1997) demonstrated that is possible to conduct operational millet yield forecasts using NDVI derived from AVHRR data in Senegal. Hobbs (1995) developed a technique to assess regional herbage biomass production using NOAA-11 NDVI data for the Central Australian region. He also demonstrated that assessment of herbage biomass in arid regions can be readily undertaken using NDVI data. In addition to NDVI, estimate of thermal condition is crucial for monitoring agricultural production. Kogan (1997) developed AVHRR-derived three-channel indices which

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account for the differences in ecosystems, climate and weather. This approach was instrumental in early drought detection, monitoring, and analysis of the impact on agriculture around the world (Unganai and Kogan 1998; Kogan 1995a, b, 1997; Seiler et al., 1998).

The objective of this research was to test the value of NOAA AVHRR indices through the performance of corn yield prediction models, in the main cropping region of Argentina. Partial results of this work have already been used in the Cordoba province of Argentina, for regional assessments of vegetation conditions and droughts (Seiler, 1997). The availability of reliable satellite derived indices should make an important contribution to the increasing demand for spatial information.

MATERIAL AND METHODS

The study was focused on the Pampean region of Argentina. The region is located between 30° and 39° latitude south, covering most of the east central area of Argentina. Agroclimate conditions such as the occurrences of thermal and water conditions in the region were described by Pascale y Damario (1988).

Satellite data were collected for the whole Argentina from the Global Vegetation Index (GVI) data set (Kidwell, 1994), which is one of the most widely used satellite products worldwide. The GVI is produced by sampling and mapping the 4-km daily radiance in the VIS (Ch1, 0.58-0.68 m), NIR (Ch2, 0.72-1.1 m), and two thermal bands (Ch4, 10.3-11.3 m; and Ch5, 11.5-12.5 m) measured on board NOAA polar-orbiting satellites, to a 16-km map. For this research it was used data of weekly GVI from April 1985 through November 1988 from NOAA-9, data from December 1988 through September 1994 from NOAA-11, and during most of 1995 to 1997 from NOAA-14. Due to uncertatinties in the 1995 data, this year was disregarded from the analysis.

The standard data preparation procedure for the 7-day composite time series included a correction for noise of VIS and NIR values following Rao and Chen (1995). The thermal bands' measurements were converted to brightness temperatures (BT) using a look-up table and a nonlinear correction was applied following Weinreb et al. (1990). From the available series, the largest and the smallest NDVI and BT values during 1985-1993 were calculated for each of the 52 weeks of the year and for each pixel. They were then used as the criteria for estimating the upper (favorable weather) and the lower (unfavorable weather) limits of the ecosystem resources. These limits characterize the "carrying capacity" of the ecosystems and the range in which NDVI and BT fluctuate due to weather changes from year to year in each ecosystem. These fluctuations were estimated relative to the maximum and minimum (max/min) intervals of both NDVI and BT variations and combined in the Vegetation (VCI) and Temperature (TCI) Condition Indices (Kogan, 1995a; Kogan, et al 1993), as follows:

$$VCI=100*(NDVI-NDVI_{min})/(NDVI_{max}-NDVI_{min})$$

$$TCI=100*(BT_{max} - BT)/(BT_{max} - BT_{min})$$

The NDVI, $NDVI_{max}$, and $NDVI_{min}$ are the smoothed weekly NDVI, its multi-year absolute maximum, and minimum, respectively; BT, BT_{max}, and BT_{min} are similar values for temperature derived from Ch4 data. The VCI/TCI approximate the weather component in NDVI and BT values. They change from 0 to 100, reflecting changes in vegetation conditions from extremely bad to optimal. After the calculation procedure of the indices, each pixel had a time series containing eleven years with 52 values (weeks) each year. By convention, data for the first week of July were assigned to week number one and week 52 corresponded to data for the last week of June of the next year.

The field data used in this study included yearly estimations of corn yield, total production, planted and harvested area, for corn growing provinces in Argentina. All the data values represented average estimates by provinces and they were available from the crop reporting division of the Ministry of Agriculture in Argentina (SAGPyA, serial reports). Data were available for the crop seasons 1985/86 to 1996/97.The corn yield of each province was normalized by dividing the yield of each year by the technology trend level, and multiplying by 100. The technology trend for each yield series was calculated as the simple regression of corn yield and years.

RESULTS AND DISCUSSION

The relationship between the values of VCI, TCI and the yield of corn at a province level is obscured by the fact that only a portion of the area of each province is under corn cultivation. Thus, in order to establish a more reliable relation, the areas for analysis were approximated geographically to a major growing area for corn, called Region 1, and to a bigger growing area as Region 2 (Fig 1). The boundaries for the region 1 were set between 32° and 36° S latitude and 60° and 65° W longitude. The second region was delimited between 30° and 38° S latitude and 59° and 65° W longitude.

Data of VCI and TCI were aggregated as the average for each of the regions for every week and year. The mean yield of corn assigned to region 1 was calculated as the average yield for the provinces of Cordoba, Santa Fe and Buenos Aires. For region 2, it was used the average yield of corn for the country.

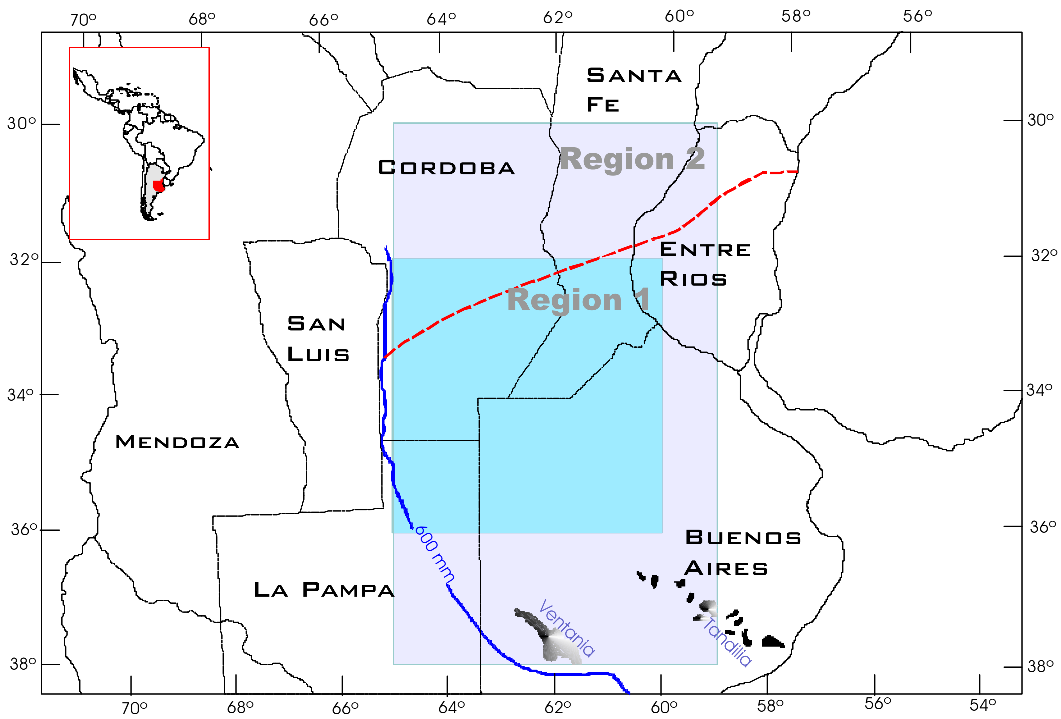

Fig. 1. Corn growing areas defined for the study as Region 1 (smaller rectangle) and Region 2 (bigger rectangle).

Weekly VCI and TCI values and corn yield for each of the regions were used in a stepwise linear regression procedure to identify predictors to be included into corn yield models. The significant variables selected for region 1 were VCI for week 23 (VCI_23) and TCI for week 29 (TCI_29). For region 2, VCI for week 24 (VCI_24) and TCI for week 27 (TCI_27) were selected. The corn yield models and indicators of the aptness of the models are presented in Table 1.

Table 1. Regional models for corn yield prediction and statistics measures for the aptness of the models

Region	Regression Models	R^2	MSE	F-ratio	P-value
1	Yield = 57.19+0.353*VCI_23+0.366 * TCI_29	0.868	38.29	26.33	0.0003
2	Yield = 70.69+0.376*VCI_24+0.152*TCI_27	0.808	25.36	16.86	0.0014

All the parameters for both models were significantly different from zero tested by a t-statistic at the $p<0.05$ level. The P-value associated with the F* test showed the significance of the overall model. The prediction bias from the predictive power of the models was measured using an independent data set generated by leaving one at a time for the whole series, a year of data out of the calculation of the model parameters. Results are shown in Table 2. The RMSE between the observed and the predictive values by the model for region 1 was 6.57 % and for region 2 was 5.18 %. These values represented 6.7 % and 5.2 % of the average corn yield of the series, respectively.

Table 2. Crop yield models performance evaluated by the error between the predicted and observed yields.

	Region 1			Region 2		
Season	Observed (% of trend)	Estimated (% of trend)	Error (%)	Observed (% of trend)	Estimated (% of trend)	Error (%)
1985/86	110.8	105.6	-4.7	108.5	102.7	-5.3
1986/87	89.3	98.7	10.5	90.2	101.4	12.4
1987/88	105.0	108.4	3.2	104.2	103.2	-0.9
1988/89	66.0	67.8	2.7	78.5	81.0	3.2
1989/90	75.4	84.2	11.7	91.2	89.4	-2.0
1990/91	104.9	110.9	5.7	104.3	109.7	5.2
1991/92	113.0	109.4	-3.2	114.2	106.8	-6.5
1992/93	109.3	107.2	-1.9	107.6	106.3	-1.2
1993/94	107.7	103.8	-3.6	102.4	105.2	2.7
1994/95	-	-	-	-	-	-
1995/96	95.5	81.1	-15.1	93.8	88.9	-5.2
1996/97	97.5	98.6	1.1	103.3	106.0	2.6

The results have proven that the applications of VCI and TCI indices to account for the climatic variability and to predict yield of corn in the main cropping area of Argentina are useful. The nature of VCI has the capability to describe the spatial differences in the productivity of the regions and the year-to-year climate variations in each region. Corn yield developed models based on VCI and TCI can provide reliable and timely yield estimates of regional agricultural production. More than 80 % of the variability in the yield of corn was explained by the VCI and TCI indices. Yield estimates can be made about two months before harvesting.

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