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MODELS FOR EVALUATING THE DYNAMICS OF MAIZE CROP AND ESTIMATING PRODUCTION BASED ON SATELLITE IMAGES

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Abstract

The study used remote sensing-based techniques to monitor a maize crop, the Pioneer 9911 hybrid, and thus predict the production for crop and farm management. The Sentinel 2 satellite system was used to obtain the satellite scenes. Satellite images were taken at 10 different times, between April 26 and October 3, 2021. Based on spectral information, the NDMI, NDVI, CIG and NBR indices were calculated, and they were used to describe the dynamics of maize crop during the study period and prediction of maize production. The dynamics of maize cultivation was quantified based on NDMI, NDVI and CIG indices in statistical accuracy conditions at the level of R^2= 0.943 to R^2= 0.976, p <0.001, and based on the NBR index at the level of R^2= 0.802, p = 0.0156. The prediction of maize production was possible based on the indices calculated in statistical accuracy conditions (p<0.001, R^2>0.990). The errors calculated between predicted production (YP) and real production (YR) varied according to the image capture time and the combination of indices used in the regression analysis.

Key words*: *crops management, maize, models, remote sensing, Sentinel 2, yield prediction

INTRODUCTION

The methods of evaluating agricultural crops have evolved a lot, from simple direct observation by the farmer, until the use of remote surveillance and monitoring techniques, based on imaging analysis [12, 15, 30, 40]. Techniques based on remote sensing and GIS have developed and became more and more accessible, due to the facilities offered by different satellite systems and the delivery of images at adequate and accessible resolutions [3, 8, 24, 26].

In addition to direct spectral information, satellite images offer the possibility to find new information, through different specific indices, in relation to the category of analyzed surface (natural areas, agricultural crops, urban ecosystems, etc.) for the purpose proposed in the study [2, 46].

Thus, the indices calculated on the basis of spectral information in different satellite systems, offer new and more precise information, with a higher refinement of analysis and evaluation of agricultural crops, in relation to natural or technological factors of influence [28, 35, 41, 46].

Various studies based on remote sensing have addressed aspects of crop monitoring [18, 22, 34], evaluation of water provision for the crops [1, 39], providing the nutrients and fertilizing crops [5, 6, 38], plant protection [13], estimation of productions [14, 23, 27] and other aspects of practical importance. Aspects related to the prediction of crop production based on remote sensing, are also of interest in relation to the agricultural products market, the sustainability of the rural environment and food security [20].

Farm and crop management based on remote sensing, benefits from real-time information with high precision and very detailed, regarding agricultural crops, in terms of physiological indices and processes, plant health, growth rate, biomass production, etc., so that timely intervention decisions can be taken for high-profitability productions [4, 29].

Crop evaluation based on remote sensing is very useful in relation to the nutritional status of plants, especially azoth (N), and nutrient supply by fertilization, in relation to the technical and economic efficiency of each agricultural crop [7, 25, 45, 47].

The monitoring of rice cultivation based on remote sensing (Sentinel-2) has facilitated the evaluation of plant phenology and production parameters, and early interventions (33 days after sowing - tillering stage) through appropriate treatments (biostimulators) led to production increases of up to 13.06% [37]. The authors communicated a culture monitoring strategy based on culture dynamics and correlations between spectral information (green, red, and NIR). Also, the authors San Bautista et al. [37] reported that a new approach (NCMI) was more effective than classical indices (NDVI, GNDVI, or EVI2), as a result of a higher sensitivity when capturing the condition of plants and culture, based on which the intervention decisions are useful / beneficial.

In the context of the interest on remote sensing in the management of agricultural crops and the facilities offered, the present study analyzed a corn crop based on satellite images in the Sentinel 2 system, evaluated the dynamics of the crop in relation to time (days) and found models for estimating the production through indices calculated on the basis of spectral information.

MATERIALS AND METHODS

The study used remote sensing techniques to monitor maize cultivation during the growing season based on calculated specific indices and to estimate maize production based on those indices. The land considered in the study, with an area of 20 ha, is located in the area of Lipova, Arad County, Romania, figure 1. The biological material was represented by the corn crop, the Pioneer 9911 hybrid, the crop being destined for grain production. The sowing was done on April 10, and the harvest on October 20, 2021. The production obtained was 9,170 kg ha^{-1}.

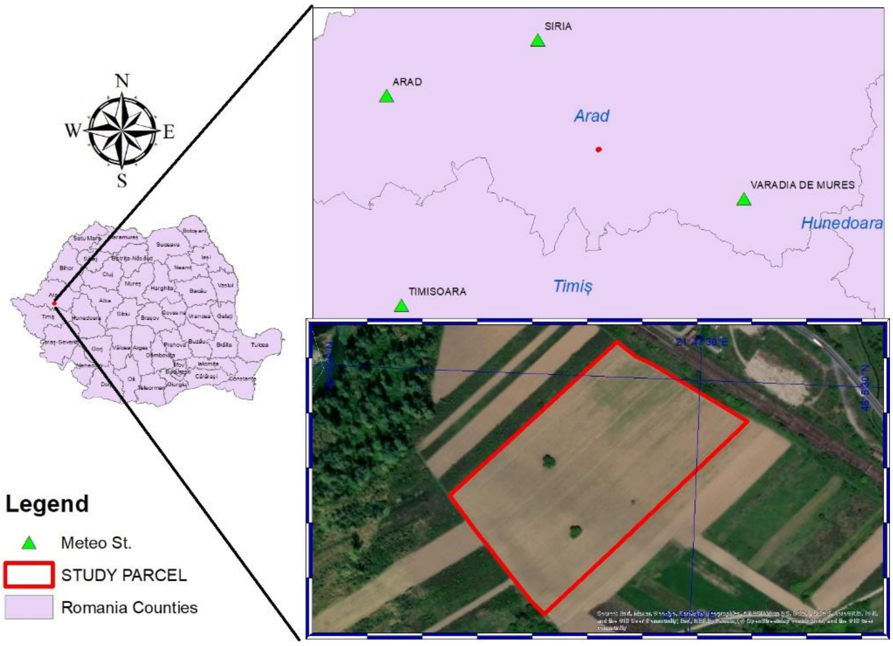


Fig. 1. Framing area and study plot, Lipova locality, Arad County, Romania
Source: Original image.

The Sentinel 2 system was used to take over the satellite scenes in order to characterize the corn crop. 10 satellite images were taken, between April 26 and October 3, 2021. Satellite images were taken at 10 moments during the vegetation period: April 26 (Id1), May 11 (Id2), May 26 (Id3), June 15 (Id4), July 5 (Id5), July 25 (Id6), August 9 (Id7), August 19 (Id8), September 13 (Id9) and October 3 (Id10). The time (T, days) was calculated for each image capture time in relation to the first image capture date.

Based on the satellite images, indices have been calculated: NDMI [42], relation (1), NDVI [36], relation (2), CIG [16, 17, 44], relation (3) and NBR [21], relation (4).

$$NDMI = (B8 - B11)/(B8 + B11) \quad (1)$$

$$NDVI = (B8 - B4)/(B8 + B4) \quad (2)$$

$$CIG = (B8/B3) - 1 \quad (3)$$

$$NBR = (B8 - B12)/(B8 + B12) \quad (4)$$

In order to evaluate the variability of the data (within each index), the coefficient of variation (CV) was calculated. The interdependent relationship between the calculated index values (correlation analysis, parameter r) was evaluated.

The variation of the index values was analyzed in relation to the time during the vegetation period (regression analysis, regression coefficient R^2, parameter p, 95%, for statistical safety). Regression analysis was used to estimate production based on the values of the indices calculated from the satellite images, taken at different moments in time (regression coefficient R^2, parameter p, 95%, and parameter RMSEP, for statistical safety). The data analysis was done in the EXCEL program (mathematical and statistical calculation module), with the PAST software [19], and the Wolfram Alpha software (2020) [43].

RESULTS AND DISCUSSIONS

Based on satellite images, spectral information was obtained (Sentinel 2 system) and NDMI, NDVI, CIG and NBR indices were calculated to characterize the maize crop, Pioneer 9911 hybrid, during the vegetation period, between April 26 and October 3, 2021, Table 1. The graphical distribution, as Matrix plot, shows the temporal variation of the index values, and highlights the minimum (blue colour) and the maximum (red colour), Figure 2.

Table 1. The values of the indices calculated for the temporal characterization of the maize crop

Image acquisition date	Trial	NDMI	NDVI	CIG	NBR	Production (Y) (kg ha^{-1})
26.04.2021	Id1	-0.1298056	0.1466207	0.2365325	-0.0279997	9,170
11.05.2021	Id2	-0.1294211	0.1498069	0.2412191	0.0235460	
26.05.2021	Id3	-0.0065019	0.2542073	0.2915165	-0.1355289	
15.06.2021	Id4	-0.0065019	0.3179364	0.5170612	0.6789103	
05.07.2021	Id5	0.1901094	0.5801357	0.5170612	0.5801357	
25.07.2021	Id6	0.3322841	0.6888322	0.5814463	0.6888322	
09.08.2021	Id7	0.3021260	0.6807519	0.5697305	0.6641069	
19.08.2021	Id8	0.3074087	0.6914967	0.5923583	0.6641069	
13.09.2021	Id9	0.1497599	0.5674268	0.4872892	0.4986275	
03.10.2021	Id10	-0.0805157	0.3557402	0.3118401	0.1913175	

Source: original data calculated based on satellite imagery.

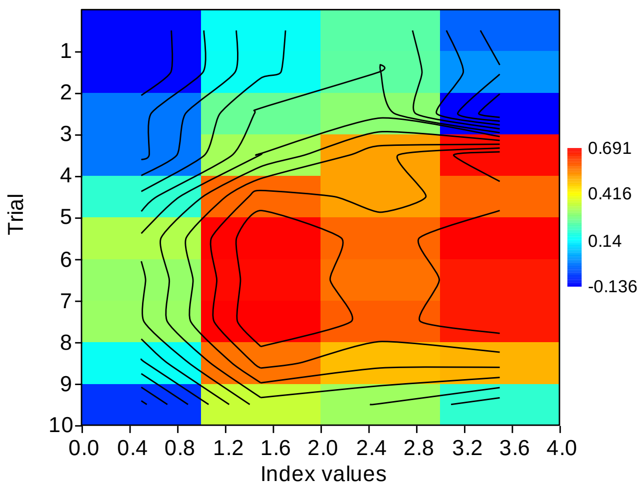


Fig. 2. Temporal variation of index values, arable land, maize crop, the Pioneer 9911 hybrid
Source: original figure.

The index values showed differentiated variability, in relation to the characteristics they express regarding the corn culture. Based on the coefficient of variation (CV), the NDMI index showed the highest variability (CV_{NDMI}=199.3487), and the CIG index showed the lowest variability (CV_{CIG} =33.7172). Indices NDVI and NBR showed intermediate variability, CV_{NDVI}=50.2002, and CV_{NBR}=86.9087.

The variation of the indices values taken into account was analyzed in relation to time, and the method used was regression analysis.

The variation of the NDMI index in relation to the time during the study period was described by equation (5), under conditions of R^2=0.964, p<0.001.

The variation of the DVI index in relation to time was described by equation (6), under conditions of R^2=0.976, p<0.001. The variation of the CIG index in relation to time, during the study period, was described by equation (7), under conditions of R^2=0.943, p=0.00038. The variation of the NBR index, in relation to time, over study periods, was described by equation (8), under conditions of R^2=0.802, p=0.0156.

As example, the graphical distributions of the NDMI and NDVI indices, figure 3, respectively of the NBR index, figure 4, was shown. In the case of the NBR index, deviations of the index values were found in the case of moments Id3 and Id4, from the theoretical model described by the graphical representation of equation (8), associated with the state of vegetation, the presence of weeds and culture maintenance works specific to that period of vegetation. Such highlights are useful as warnings about culture management.

$$NDMI = -0.7288\,E-07x^3 + 0.0001223\,x^2 - 0.0005697\,x - 0.1324 \quad (5)$$

$$NDVI = -7.503\,E-07x^3 + 0.0001263\,x^2 - 0.0004018\,x + 0.1311 \quad (6)$$

$$CIG = -3.436\,E-07x^3 + 3.685x^2 + 0.003621\,x + 0.2055 \quad (7)$$

$$NBR = -6.53\,E-07x^3 + 6.45\,E-05x^2 + 0.008317\,x - 0.1171 \quad (8)$$

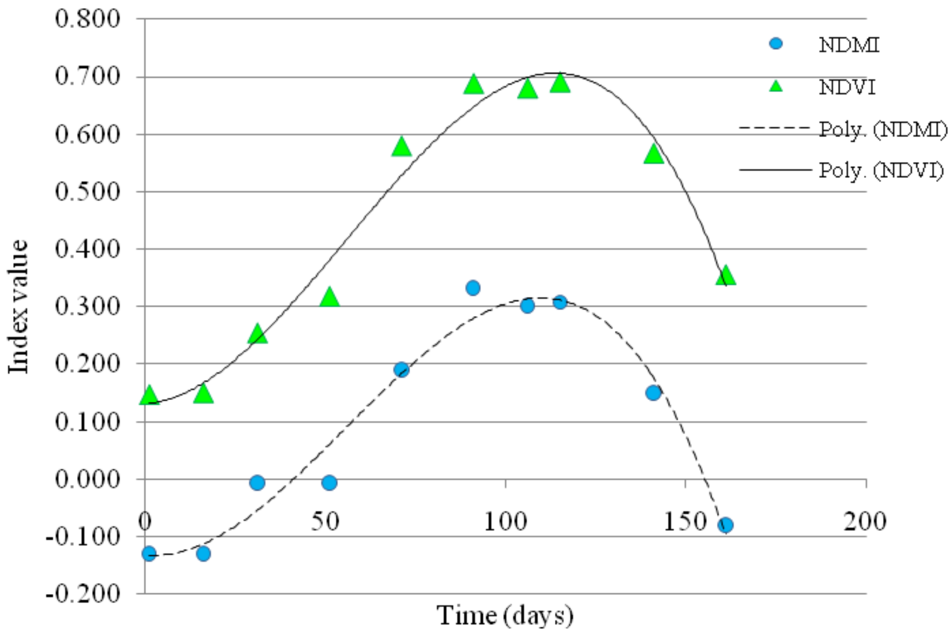


Fig. 3. Graphic distribution of NDMI (blue points) and NDVI (green points) index values in relation to corn crop time, the Pioneer 9911 hybrid
Source: original graph.

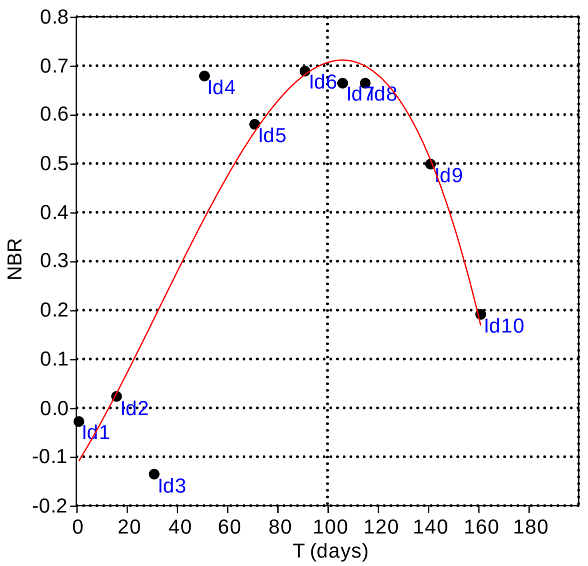


Fig. 4. Graphic distribution of NBR index values in relation to time, maize crop, the Pioneer 9911 hybrid
Source: Original graph

The regression analysis facilitated the obtaining of a general equation, equation (9), for predicting the maize production based on the indices calculated from the satellite images, in conditions of statistical accuracy; R^2=0.999, p<0.001 under the conditions of using NDMI and NDVI indices, and CIG and NBR indices for production prediction; R^2=0.992, p<0.001 under the conditions of using NDVI and NBR indices for production prediction.

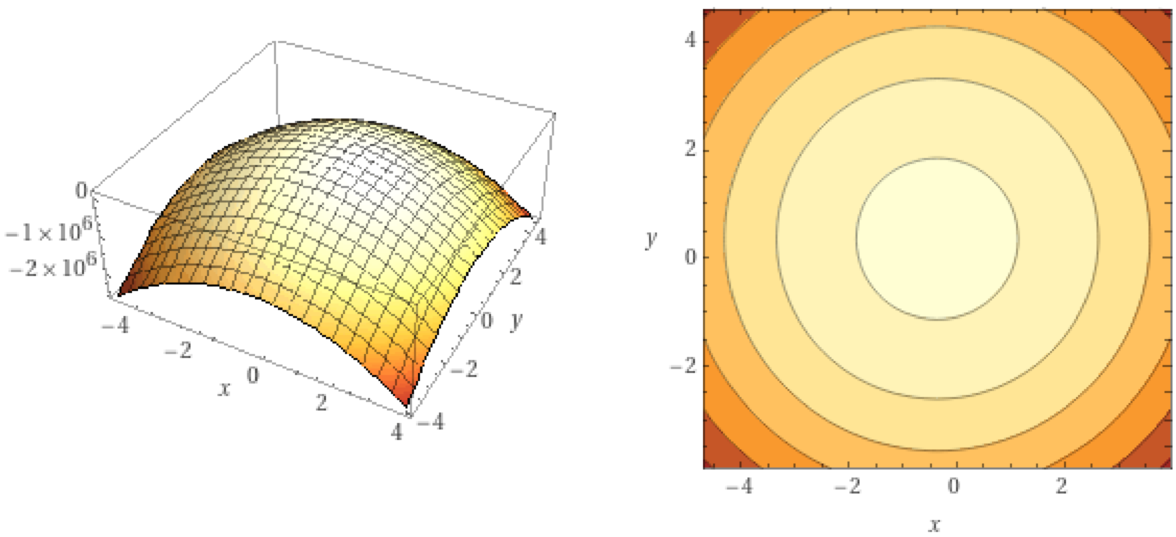
The values of the coefficients of equation (9), in relation to the combination of indices (x,y) used in the production prediction, are shown in Table 2. Graphical representation of production (Y), in the form of 3D models and in the form of isoquants, in relation with the indices used for prediction, is shown in Figures 5 - 8.

$$Y = ax^2 + by^2 + cx + dy + exy + f \quad (9)$$

Table 2. The values of the equation (9) coefficients

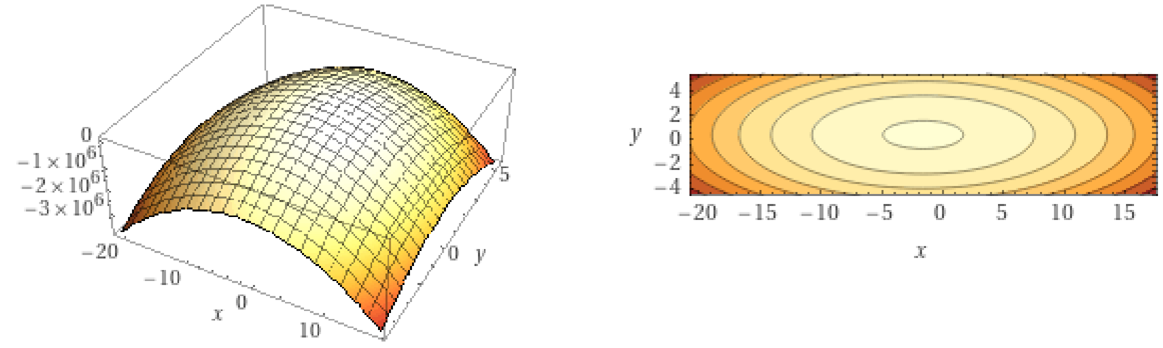
Coefficients of the equation (9)	Equation (9) where			
	x=NDMI y=NDVI	x=NDMI y=CIG	x=NDVI y=NBR	x=CIG y=NBR
a	-75,081.714842	-6,891.227446	-184,135.879732	-115,071.357980
b	-75,958.959869	-55,293.212306	-11,459.093204	-17,158.994608
c	-54,152.888015	-21,970.044962	84,748.843528	65,946.834016
d	53,856.744776	46,106.569634	-38,598.258185	-26,531.322385
e	150,350.421249	47,150.749243	148,673.198434	90,327.705029
f	0	0	0	0

Source: Original data obtained by calculation.



(a) (b)

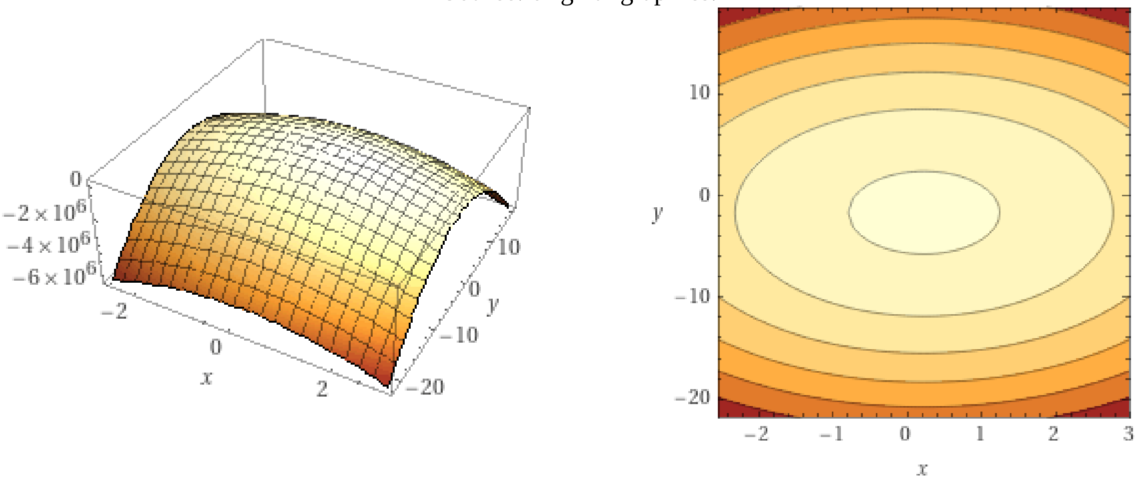
Fig. 5. 3D model (a), and in the form of isoquants (b), regarding the variation of maize production, the Pioneer 9911 hybrid, in relation to indices NDMI (x-axis) and NDVI (y-axis)
Source: original graphics.



(a) (b)

Fig. 6. 3D model (a), and in the form of isoquants (b), regarding the variation of maize production, the Pioneer 9911 hybrid, in relation to indices NDMI (x-axis) and CIG (y-axis)

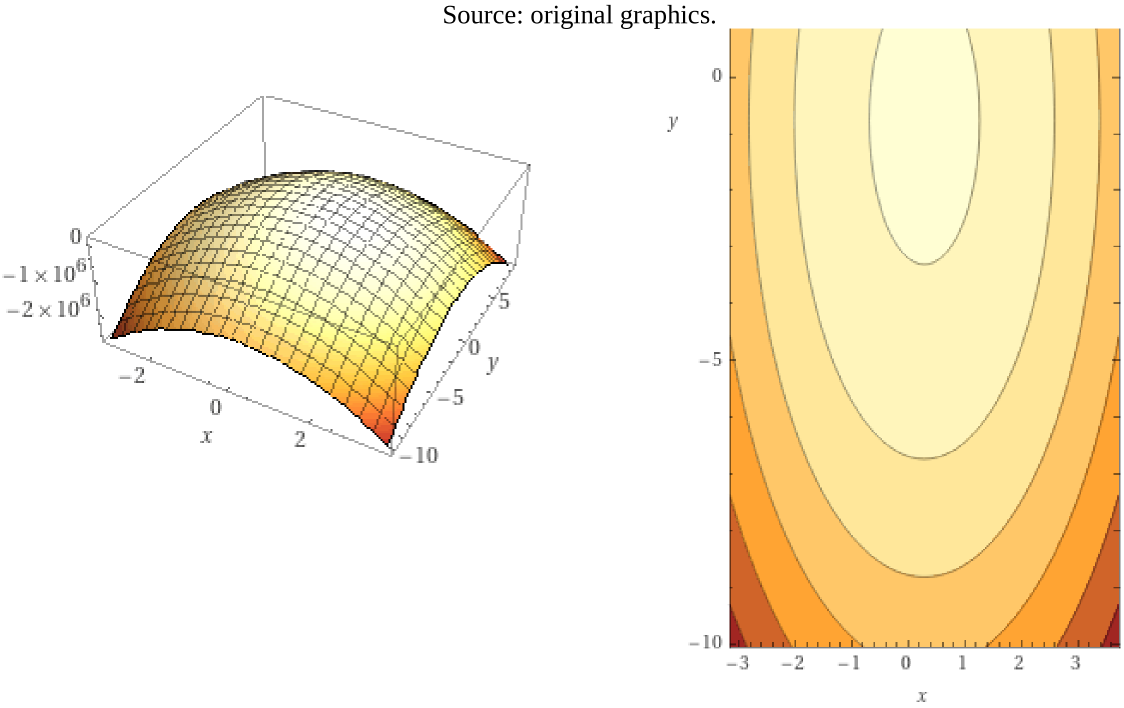
Source: original graphics.



(a) (b)

Fig. 7. 3D model (a), and in the form of isoquants (b), regarding the variation of maize production, the Pioneer 9911 hybrid, in relation to indices NDVI (x-axis) and NBR (y-axis)

Source: original graphics.



(a) (b)

Fig. 8. 3D model (a), and in the form of isoquants (b), regarding the variation of maize production, the Pioneer 9911 hybrid, in relation to indices CIG (x-axis) and NBR (y-axis)

Source: original graphics.

Prediction errors were calculated between real production (YR) and predicted production (YP) based on the indices considered, and calculated based on images taken at different times during the vegetation period, Table 3, with graphical representation in Figure 8.

Table 3. Production prediction errors in relation to image capture time and index combination used

Trial	Real production (Y)	Production prediction error			
		YP1	YP2	YP3	YP4
		x=NDMI y=NDVI	x=NDMI y=CIG	x=NDVI y=NBR	x=CIG y=NBR
	(Kg ha^{-1})	Kg			
Id1	9,170	-3.662	-69.781	-241.146	121.792
Id2		29.333	-9.573	-997.201	-79.163
Id3		-287.375	-374.909	373.211	-12.555
Id4		312.937	-128.807	-233.686	-48.867
Id5		83.158	96.213	1,811.730	92.414
Id6		15.793	-6.422	356.106	31.800
Id7		**0.477**	**-0.139**	-283.190	39.748
Id8		-31.353	-79.172	-1,026.688	-136.500
Id9		-84.408	163.921	-398.477	93.367
Id10		-56.698	371.328	**-9.381**	-110.133

Source: Original data from the calculation

From the analysis values obtained, negative and positive differences were observed, variable in order of size, in relation to the pair of indices used in the regression analysis and the moment of images acquisition on the basis of which they were calculated.

The prediction of production in agricultural crops is of interest in relation to organizing the harvesting process, transport and storage of production, in relation to the processing or exploitation of agricultural production, in relation to food safety [20, 31, 32].

Prediction of production is also important in relation to the behaviour of genotypes of cultivated plants [9], with the performance evaluation of agricultural technologies practiced [10, 11, 33] formulating models for correcting and optimizing technological sequences. Depending on the moment of production prediction and elements identified as potentially limiting, corrective measures can be taken in order to increase crop performance [4, 29].

Li et al. (2022) [25] used regression analysis and machine learning methods to estimate N content, N absorption in maize plants, and biomass production under conditions of statistical safety.

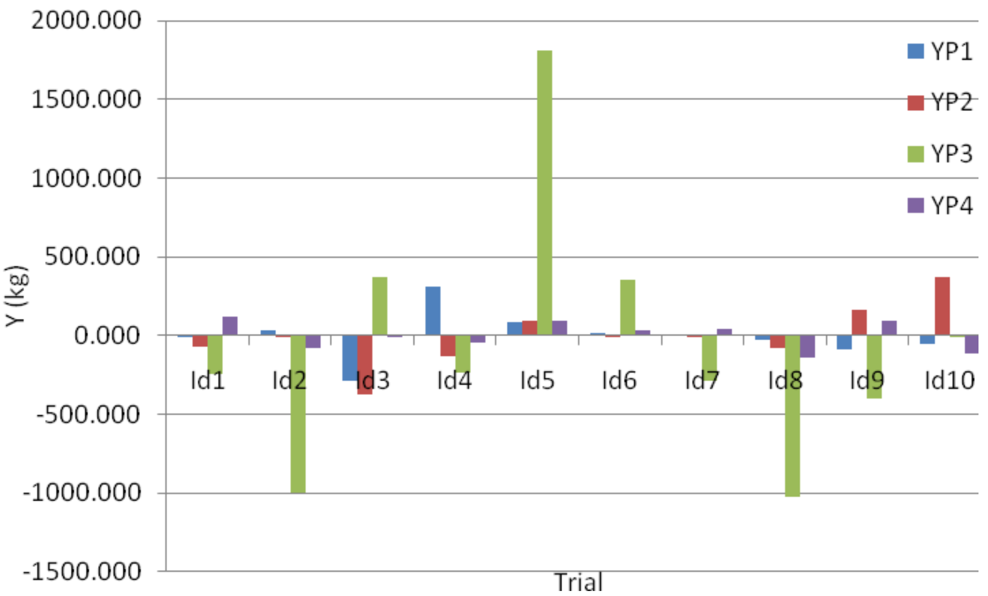


Fig. 8. Graphical representation of prediction errors for maize production, the Pineer 9911 hybrid, based on satellite images (YP1 – estimated production based NDMI and NDVI; YP2 – estimated production based on NDMI and CIG; YP3 – estimated production based on NDVI and NBR; YP4 – estimated production based on CIG and NBR)
Source: original graph.

They communicated different levels of safety (R^2=0.74 to R^2=0.90, respectively R^2=0.840 to R^2=0.930) in relation to the working mode, and high levels of safety were recorded in the case of an integrated approach, when complex information of type (plant genetics - environmental factors – management) were approached together.

In the context of the present study, regarding the safety of the prediction and the analysis of prediction errors in relation to the time of acquiring the images and the indices used, favourable combinations can be found (moment of taking the images and appropriate indices) to provide the most reliable predictions. In relation to these aspects, the management of the maize crop can be adapted, in the context of the purpose and the study conditions, in order to achieve a certain performance in terms of production and profitability.

CONCLUSIONS

Remote sensing imaging analysis, the Sentinel 2 system, has facilitated the obtaining of satellite images that captured the dynamics of maize cultivation under the study conditions, and the calculation of specific representative indices.

The dynamics of the index variation was evaluated in relation to the time during the study period, and based on the indices it was possible to assess the vegetation status of the maize crop, highlighting some deviations from the theoretical models in the case of the NBR index.

The regression analysis facilitated the prediction of the production based on the calculated indices, in conditions of statistical accuracy. The calculated prediction errors varied with respect to the image capture time and indices used in the regression analysis, which facilitates the choice of the appropriate combination (image capture time / index) for high-precision production prediction.

The information obtained can be considered for the improvement of the technology for maize cultivation and the proper management of the farm and agricultural crops.

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