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Research Paper

Predictive Analytics of Plots For Soybean Production

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ABSTRACT

This study is to determine the feasible productivity of a plot of land in large fields where the quality of the soil and the weather conditions fluctuate every year, hindering optimum soybean production practices. The aim is to predict 8 sceneries through the artificial neural network model and study its reliability. Then predict 7 feasible sceneries to achieve a good sowing strategy on certain plots of land and with certain types of seeds. Finally, to make a prediction using the average historical rainfall data collected during the studied months and to observe the fluctuations on the yield in accordance with previous predictions. The artificial neural network is the method used and it was provided by soft RISK Industrial 7.6 (Neural Tools). The result is going to be compared with the data collected from the company "Nueva Castilla" of Trenque Lauquen (Buenos Aires province, Argentina) to determine the practical and technical feasibility of the model. These data correspond to more than 17 years of climate and weather analysis, soil and soybean yield with different types of seeds.

Key words: Artificial neural network; soybean (glycine max); rainfall, yield prediction.

INTRODUCTION

The estimation of agricultural production is necessary for the planning that has to be done by the private and the public sector as well; from food security and environmental sustainability early warning to the ratification of biophysics methods in crop production (Lyle, 2013). Anticipated and reliable information on the productivity of crops has influence over the management of crop tasks, storage, imports and exports, means of transport and commercialization (Lobell, 2003). Extensive agriculture is the main production system used in the centre region of Argentina and the most important source of income. Soybean [*Glycine max* (L) Merrill] and corn (*Zea mays* L) crops are the main source of agricultural activity during summer, reaching 86% of the total cultivated fields in Argentina. Among those crops, the most important one is the soybean crop, achieving 19.781.812 sown hectares during the 2013/2014 period, especially in the Córdoba province where 26% of the total soybean crops have been sown (Minagri, 2015). In the last few years, performance information is generally gathered from models either with information on crop management or climate and soil data, among others. Several studies show the importance of crop growth models in order to predict productivity (Batchelor, 2002).

Due to the effects of the genotype, the environment and their interaction, soybean production fluctuates and the environmental impact is responsible for most of these fluctuations. Soil properties (physical and chemical) and meteorological variables (radiation, water and thermal regimes) determine different environments for soybean crops (Salvagiotti, 2010). Using simple mathematical models, it is feasible to describe properly the soybean and corn production to be obtained through satellite images gathered two or three months before the harvest (Bocco, 2015). The aim of this research is to predict through an artificial intelligence model, the soybean production in known areas where information has been gathered through years and where the main variable are soil characteristics, the type of seed, the sowing date and rainfall data during the harvesting season.

MATERIALS AND METHODS

NeuralTools (PALISADE) was used for the prediction of soybean production which is a Neural Network software of Microsoft Excel. Neural networks are able to automatically discover in-out relations based on empirical information,

Year	Class	Var	Cycle	Crop ant	Date	Sept	Oct	KGS/HA
2001/02	B	DM 4800	LARGO	MAIZ	21-31 OCT	214	128	2463
2001/02	C	DM 4800	LARGO	MAIZ	21-31 OCT	214	128	3128
2001/02	B	DM 4800	LARGO	MAIZ	21-31 OCT	214	128	3671
2001/02	A	DM 4800	LARGO	MAIZ	21-31 OCT	214	128	4512
2001/02	A	DM 4800	LARGO	MAIZ	21-31 OCT	214	128	3266
2001/02	A	DM 4800	LARGO	MAIZ	21-31 OCT	214	128	4058

Figure 1: Database used by the network from 2001/02 period..

Test 1	A	DM 4800	LARGO	PAST	1-10 NOV	31	133
Test 2	B	DM 4800	LARGO	VI	21-31 OCT	50	71
Test 3	C	DM 4800	LARGO	PAST	1-10 NOV	50	71
Test 4	B	DM 4800	LARGO	SOJA	21-31 OCT	19	173
Test 5	B	DM 3700	CORTO	MAIZ	21-31 OCT	97	94
Test 6	A	DM 3700	CORTO	MAIZ	21-31 OCT	97	94
Test 7	C	DM 4800	LARGO	PAST	1-10 NOV	55	141
Test 8	C	DM 4800	LARGO	FINA/SOJA	21-30 NOV	45	58

Test 1	A	Predic	3919	96,66%
Test 2	B	Predic	2942	98,58%
Test 3	C	Predic	2116	92,18%
Test 4	B	Predic	1758	98,47%
Test 5	B	Predic	3216	92,70%
Test 6	A	Predic	3930	99,73%
Test 7	C	Predic	434	96,20%
Test 8	C	Predic	2690	96,20%

Figure 2a and b: Accuracy of the model.

due to its learning skills depending on examples. The database used corresponds to an agricultural company located in the city of Trenque Lauquen, Buenos Aires, Argentina. This company gatheres sowing and harvesting information corresponding to more than 17 years. The company identifies each plot with a private code, each code is assigned a letter A, B or C that corresponds to the soil quality. It is also considered rainfall during the months which are key, Septemeber and October, for moisture accumulation before sowing; the preceeding crop to the period of sowing of each field (the sowing date corresponding to ten-day periods); the type of crop (whether it corresponds to a long or short cycle) and finally the database from which the two types of seeds DM 3700 and DM 480 were chosen, due to the fact that both were tried within a more-than-five-year correlation and that allows an anlysis with more information for the neural network. Figure 1 shows the database to be used by the network from the period of 2001/02 to 2015/16.

The database has 311 sceneries gathered from the 2001/02 period to the 2015/16 one, with variations on the soil, seeds, sowing dates and external factors that exceed the farmer's decisions, such as rainfalls.

RESULTS

Three predictions were carried out for the first one 8 sceneries were simulated so as to verify the soundness and accuracy of the model. Variations between 5 to 6% are accepted for type-A soils, while between 15 and 19% for type-B and type-C soils due to the fact that conditions are less favourable for these crops and foster more fluctuations on the production. As it is observed on the earlier charts the predictions done for type-A soil fields were 96.66% and 99.73% accurate. For type-B soil they vary from 92.70% to 98.58%, while for type-C soil they vary from 92.68% to 96.20%. Figure 2a and b shows the accuracy of the model.

PREDIC 1	A	DM 3700	CORTO	MAIZ	21-31 OCT	66	45
PREDIC 2	B	DM 3700	CORTO	MAIZ	1-10 NOV	66	45
PREDIC 3	C	DM 3700	CORTO	MAIZ	21-31 DIC	66	45
PREDIC 4	A	DM 4800	LARGO	PAST	21-31 OCT	66	45
PREDIC 5	B	DM 4800	LARGO	PAST	1-10 NOV	66	45
PREDIC 6	C	DM 4800	LARGO	PAST	21-31 DIC	66	45
PREDIC 7	B	DM 3700	CORTO	Soja	1-10 NOV	66	45

PREDIC 1	A	21-31 OCT	DM 3700	3622
PREDIC 2	B	1-10 NOV	DM 3700	2861
PREDIC 3	C	21-31 DIC	DM 3700	2854
PREDIC 4	A	21-31 OCT	DM 4800	3455
PREDIC 5	B	1-10 NOV	DM 4800	2508
PREDIC 6	C	21-31 DIC	DM 4800	2326
PREDIC 7	B	1-10 NOV	DM 3700	2585

Figure 3a and b: Prediction of crop yield.

Test average 1	A	DM 4800	LARGO	PAST	1-10 NOV	49	94
Test average 2	B	DM 4800	LARGO	VI	21-31 OCT	49	94
Test average 3	C	DM 4800	LARGO	PAST	1-10 NOV	49	94
Test average 4	B	DM 4800	LARGO	SOJA	21-31 OCT	49	94
Test average 5	B	DM 3700	CORTO	MAIZ	21-31 OCT	49	94
Test average 6	A	DM 3700	CORTO	MAIZ	21-31 OCT	49	94
Test average 7	C	DM 4800	LARGO	PAST	1-10 NOV	49	94
Test average 8	C	DM 4800	LARGO	FINA/SOJA	21-30 NOV	49	94

		Model
Test average 1	3435	61,96%
Test average 2	3347	95,36%
Test average 3	1707	94,72%
Test average 4	3307	59,88%
Test average 5	3394	98,96%
Test average 6	3973	90,28%
Test average 7	1707	19,74%
Test average 8	2780	73,15%

Figure 4a and b: Comparison of results.

Once the accuracy of the model was verified, the prediction was done taking into account real sceneries in order to be compared with the current year. The prediction of crop yield is shown in Figure 3a and b. It was also considered the possibility of obtaining a prediction as regards the productivity at the moment of deciding on the tilling using the historical rainfall average of each month for each farmer's choices. The scenery that was established meets the same conditions where the soundness of the model of the neural network was tested. Therefore, it possible to compare the results obtained. The comparison of the results is seen in Figure 4a and b.

DISCUSSION

It was verified that the neural network model was consistent and accurate during the first simulation. Take into account that the accuracy of it varies between 0.27 and 3.34% for type-A soils, being this acceptable for agricultural standards. For type-B and type-C soils fluctuation increases and varies between 1.48% and 7.30% for type B and 3.80% to 7.42% for type C, being this also acceptable for these types of soils given the fact that they may vary between 15-19%.Differences on the results of types A, B and C depend on unfavourable characteristics for crops, being B and C more susceptible to external conditions, such as rainfalls. For the prediction of the 7 sceneries provided by the farmer the results were as follows. The production corresponding to type-A soils was of 3622 kg for DM 3700 and 3455 kg for DM 4800 during the same sowing. From the agronomical point of view, the results were appropriate as regards the established conditions. For type-B soils 2861 kg and 2585 kg were obtained for DM 3700, and 2508 kg for DM 800 during the same sawing period, being such results acceptable and steady as regards the soil characteristics. Finally, for type-C soils 2854 kg were obtained for DM3 700, and 2326kg for DM 4800 during the same period. The second result is coherent as regards the type of soil, and the first one is optimistic taking into account the quality of it. The high variability between one result and the other one corresponds to the characteristics of the type of soil. Using the historical rainfall average, the aim of the model was to obtain the production corresponding to different types of soil. The results were compared with the trial of the model where accuracy was verified in accordance with the neural network (Figure 2a and b) and then with real sceneries. During the tests 2, 3, 5 and 6 variations were between 1.04 and 9.32% (ideal results.) But for the rest of the sceneries variations fluctuated from 26.85 to 80.26%. As in the 50% of trials, results vary hugely and using historical rainfall averages turns the model volatile and does not gather coherent results, not even within the acceptable agricultural standards.

CONCLUSION

It has been shown the viability of the neural network model for the prediction of soybean yield. It is necessary to have a large database in order to train the model to be more accurate. Variations obtained were within the acceptable agricultural standards; therefore, the model can be useful for a company at the moment of deciding on the plots, the type of seeds and the sowing date. The use of the historical rainfall average is dismissed for the evaluation of the productivity of the sceneries since it varies greatly. Future research will take into account the possibility of using the neural network model for another crop such as corn (Zea mais) where variations are greater from the agricultural point of view, and it is more difficult for the farmer to estimate the productivity.

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