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RESEARCH PAPER

Profit maps for precision agriculture

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Abstract

C.L. Bazzi, E.G. Souza, R. Khosla, M.A. Uribe-Opazo, and K. Schenatto. 2015. Profit maps for precision agriculture. Cien. Inv. Agr. 42(3): 385-396. During the last few years, yield maps have become economically feasible for farmers due to technological advances in precision agriculture. However, evidence of yield profitability is still uncertain, and variability in yield has seldom been correlated to variability in profits. Differently from yield maps, profit maps can supply additional information about the economic return for each particular area of a field. The objective of the present work was to study how management decisions can be facilitated by transforming yield-map datasets into profit maps and the importance of the selection of interpolator type. Yield and profit maps were generated for each data set (three soybean fields and one corn field) using the inverse of the distance (ID), the inverse of the square of the distance (IDS) and kriging (KRG) as interpolation methods. It can be concluded that profit maps are an important tool for the diagnosis of the spatial variability of economic return because they can assist farmers with management decision-making. The impact of the interpolator type was less than 200 kg ha^{-1} for the yield and US$ 30 ha^{-1} for the profit, indicating that the choice of interpolator type is of secondary importance. In addition, the profit maps showed large variability that would not be easily found if only yield maps were analyzed.

Key words: Precision agriculture, profit map, profitability map.

Introduction

To remain viable, agriculture in different locations must offer returns that are competitive with those from alternative investments and are sufficient to cover the producers' financial obligations (Blank *et al*., 2005). Thus, technological advances in precision agriculture have made yield maps accessible to farmers. Yield maps can be easily generated after data collection by a yield monitor and can be used to integrate the effects of several spatial variables such as soil properties, fertilizer rates, topographical attributes, atmospheric conditions, the occurrence of diseases and pest infestations.

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According to Kravchenko *et al*. (2005), interactions among different factors such as topography, soil properties, and management practices can result in the spatial variability of crop yield, so the quantitative characterization of this spatio-temporal variability by means of a yield map is an important factor for precision-agriculture applications. Ping and Dobermann (2005) affirmed that yield mapping is one of the most widely used precision farming technologies, and Swinton and Lowenberg-DeBoer (1998) stated that it is profitable when it reveals yield patterns that can be managed at acceptable costs and when the information has compensating value off the field. Swinton and Lowenberg-DeBoer (1998) also remarked that the management of yield variability includes not only the site-specific application of inputs but also field-specific improvements such as drainage, leveling, windbreaks and fences.

According to Massey *et al*. (2008), transforming the yield data to another economic metric such as gross revenue, profit and internal rate of return has already been investigated, and corresponding revenue maps and yield maps may have different scales but the general "topography" will be proportional. Ten years (1993-2002) of clean yield map data for corn, soybeans, and grain sorghum were collected for a 35.6-ha claypan-soil field in Missouri. The improvement in management decisions by transforming the database of yield maps of various crops from the same field into profit maps to indicate profitability zones was investigated. The authors stated that profit maps incorporate costs and revenues, overcoming the problems of revenue maps because they include sufficient economic information to permit the aggregation of several years of data for different crops on the same field. They concluded that profit maps augment the use of yield maps by allowing the aggregation and comparison of yield data across crops and across years with a metric (e.g., dollars) that is useful for managerial decision-making; by incorporating cost and price data, profit maps allow the decision maker to see what areas of the field were above or below economic benchmarks across years. On the other hand, individual crop profit maps allow the farm manager to assess how specific areas of the field differ in profitability by crop over the years.

Marinoni *et al.* (2002), in Australia, developed a system to produce maps of agricultural profit on a continental scale. The process used data collected by a variety of institutions on different scales, such as information about land use, yield, production costs and revenue. The system was well-suited for various land use management and economic scenarios and represented a step forward regarding a scenario impact assessment of agricultural profits.

Practical problems with creating profit maps include the choice of crop prices and input costs necessary to estimate profit. Yang *et al*. (2002) created profit maps for ten grain sorghum (*Sorghum vulgare* Moench) fields, with areas of 7 to 26 ha, using representative high and low prices to evaluate the impact of price in a breakeven analysis. The results indicated that a high spatial yield variability, high production costs, and low resale prices result in significant profit variability and low economic returns for grain production in south Texas.

Yang *et al*. (2002) affirmed that spatial variability of yield implies variable economic returns and net profit throughout the field; however, yield variability has rarely been correlated with profit variability. They stated that profit maps can be generated from data provided by yield monitors, crop prices, and production costs, and unlike yield maps, profit maps can provide additional information related to the economic return for each area within a field, enabling the farmer to make better decisions concerning management. Finally, they also remarked that profit maps can be used to identify stands, or even parts of stands within a field, that consistently have a low production profile. These areas could be properly used for production of silage, the cultivation of other crops, or left fallow. However, a more complete analysis should also include a soil map.

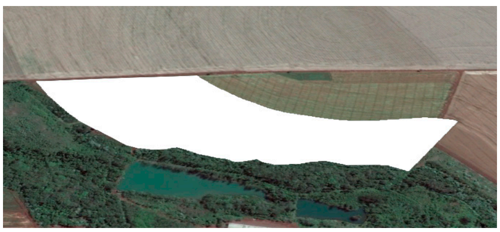
Starting from a base of georeferenced yield data and using a geographic information system (GIS), yield maps can be generated through interpolation. Yang *et al*. (2002) remarked that inverse distance methods and kriging could produce cartographically acceptable yield maps. According to Jones *et al*. (2003), numerous studies have compared interpolation methods using a variety of data (e.g., atmospheric data, clay content, soil pH, rain precipitation data, elevation data, chemical data, etc.). Not all of these studies included inverse distance weighting (IDW) in their comparisons. The accuracy of each scheme was gauged using a cross-validation approach. The studies that included IDW was better in several cases, even though kriging proved better "on average". Many researchers (Birrell *et al*., 1995; Murphy *et al*., 1995; Jaynes and Colvin, 1997; Yang *et al*., 1998; Yang *et al*., 2002) used geostatistics to understand spatial yield variability. However, few studies have compared different methods for interpolating yield data (Coelho *et al*., 2009).

Another fact that should be emphasized is that even in situations for which the sampling density is high, such as with yield monitors, the choice of the interpolator is an important decision because an interpolator can be either exact or inexact. An exact interpolator produces values identical to the measurements at the sampled locations. However, most interpolators used to manipulate yield data are inexact, affecting the minimum, maximum and average values, and changing the asymmetry and kurtosis distributions.

The objective of this research was to investigate, via four case studies, how management decisions can be facilitated by transforming a yield-map dataset into a profit map, as well the importance of the selection of the interpolator type.

Material and methods

The corn and soybean yield in four crop areas (Figure 1) located in the rural area of the city of Cascavel (24 57' S and 53 27' W, average elevation of 750 m), in the state of Parana, Brazil, were evaluated. A New Holland®TC 57 combine



a) Soybean- 2003

b) Corn-2004

c) Soybean-2006

d) Soybean-2007

Figure 1. Experimental areas used in the experiments located in the rural area of the city of Cascavel, state of Parana, Brazil.

equipped with an AgLeader® PF 3000 yield monitor was used for the harvest. After data collection, sample points that had very high or very low yields (extreme values) were eliminated following the procedure outlined by Khosla and Flynn (2008). These points were most likely affected by sources of error, such as timing delays, loading and unloading times, GPS positioning, or a smaller actual harvesting width than that indicated by the monitor. Data that showed a very low or very high water content due to a moisture sensor reading error were also eliminated.

The maps were constructed using data collected for each area (Table 1) that had a sampling density higher than 175 points ha^{-1}. Although the sampling density was well above the minimum of 2.5 points ha^{-1} necessary to build a thematic map (Wollenhaupt and Wolkowski, 1994), the effect of the interpolator type used to construct the yield map was evaluated because the interpolator typically does not reproduce the sampled value, affecting the minimum, maximum and average values, and changing the asymmetry and kurtosis distributions. Another question involves the number of yield maps to use. Several studies (Lamb *et al*., 1997; Dobermann *et al*., 2003; Schepers *et al*., 2004; Massey *et al*., 2008) indicated that 5 years or more of yield data may be required to represent the yield variability for each crop grown in a field. However, only one year of yield data was available, so that was used. This limited availability was not considered a problem because the focus of this study was to explore the importance of a profit map, not to make real decisions for the fields. If a farmer wants to make decisions based on a profit map, more yield maps should first be collected for the database. Other researchers, such as Yang *et al*. (2002), have also used only one year yield data for profit analysis.

Table 1. Production cost of the crops (US$ ha^{-1}).

Culture/ Harvest	Soybean-03	Corn-2004	Soybean-06	Soybean-07
Production cost	270.90	366.90	641.28	632.35

Source: SEAB/PR (2015).

The data were statistically analyzed via an exploratory analysis by computing the mean, median, quartile, minimum, maximum, standard deviation and coefficient of variation (CV). The sampling coefficients of asymmetry and kurtosis were compared with the confidence intervals generated for different sizes of samples, indicating a normal probability distribution (Jones, 1969). The Anderson-Darling and Kolmogorov-Smirnov tests were used to verify data normality at a 5% probability. Data were tested for normality by at least one test before fitting. Outliers were verified via box-plot graphs. Spatial dependency was measured by the percent nugget effect (%NE) and classified according to Cambardela *et al*. (1994) using the following intervals: %NE $\leq$ 25% - strong spatial dependence, 25% $\leq$ %NE $\leq$ 75% - moderate spatial dependence and %NE $\geq$ 75% - weak spatial dependence.

Because agricultural prices frequently fluctuate mainly due to seasonal variation and demand, the best economic time for the sale of a harvest is difficult to predict and affects the profit (Eq. 1) and the difference between the gross income and the total cost. A more detailed description of agricultural profitability can be found in Yang *et al.* (2002):

$$P = Y * PP - \mathrm{Pr}_C \qquad [1]$$

where P = profit; Y = yield (ton ha^{-1}); PP = sale price of the product (US$ ton^{-1}); Pr_c = production cost (US$ ha^{-1}).

The production cost includes fixed costs (depreciation of machinery and implements, depreciation of improvements and installations, systematization and soil correction, capital, and insurance) and variable costs (operating machinery and implements, improvements of maintenance expenses, labor, seeds, fertilizers, pesticides, general costs, external transport, technical assistance, insurance, and interest). The costs were as reported by the Secretariat of Agriculture and Supply of Paraná, Brazil (SEAB/PR - Secretaria da Agricultura e do Abastecimento do Paraná, 2015).

The production cost (Table 1) and sale prices of the product (Table 2 and 3) during the harvest month and during the subsequent five months were used to study the dependence of profit on the selling season. It is worth considering that profit and profitability are different things; the latter is the earnings percentage obtained on the production costs. Because yield is often a variable with spatial dependence and profit (P) is a function of yield, it can be concluded that P has a spatial dependence, and a profit map is an important tool for economic analysis.

In this work, the inverse of the distance weighted (IDW), inverse of the distance weighted square (IDS) and kriging (KRG) were the interpolation methods used to generate the values for a 5×5 m grid using the software ArcView 9.2. The twelve nearest neighbors (default value) were used to interpolate the yield data using IDW and IDS. These are the most commonly used interpolators (Jones *et al*., 2003) and have sufficient accuracy and reliability. In addition to evaluating the performance of these interpolators, we were interested in whether the use of ordinary kriging (semivariance building on Matheron's classical formula adjusted with ordinary least squares), which is considered the best interpolator, is justified because it is more complicated and laborious to implement.

The mean absolute difference (MAD, Equation 2), which computes the mean value of the difference among each interpolation method, was used to compare the effect of the interpolator on the yield and profit maps. Three comparisons were used for each variable in the analysis (yield or profit) - KRG and IDS, KRG and ID and IDS and ID. The use of kriging is justified because it is a measure in the same unit of the analyzed variable. The MAD tends not to penalize large local deviations between observed and predicted values as much as the other methods.

$$MAD = \frac{\sum_{i=1}^{M} \left| \hat{Z}_i - \hat{Z}_i^* \right|}{M} \qquad [2]$$

where $\hat{Z}_i^*$ is the estimated value of the response variable (yield or profit) at the location i on the reference map, $\hat{Z}_i$ the value of the response variable at location i on the map to be compared, and M is the total number of interpolated locations on the reference maps.

Results and discussion

Descriptive statistics for the yield data (Table 4) show that mean soybean yields varied considerably from a low of 1,903 kg ha^{-1} (soybean-03) to a high of 3,852 kg ha^{-1}(soybean-07). Corn had an average yield of 5,549 kg ha^{-1}. The variability in soybean yield was inversely proportional to the yield; fields with higher yields had less variability than fields with low yields. The CV varied from 13.1% for Soybean-07 to 28.3% for Soybean-03 and corroborates the premise that even in small

Table 2. Selling price of corn (US$ ton^{-1}).

Year	July	August	September	October	November	December
2004	88.00	85.00	87.67	83.00	82.33	79.83

Source: SEAB/PR (2015).

Table 3. Selling price of soybeans (US$ ton^{-1}).

Year	March	April	May	June	July	August
2003	188.50	199.66	189.00	192.83	182.17	184.33
2006	181.83	180.00	173.33	191.00	188.17	186.33
2007	232.50	223.00	233.67	242.33	245.33	256.50

Source: SEAB/PR (2015).

Table 4. Descriptive statistics of the yield (kg ha^{-1}) data from the four sites used in this study

Field	Min	Mean	Median	Max	StDev[1]	CV(%)[2]	Skewness[3]	Kurtosis[4]
Soybean-03[5] (14.8 ha)	675	1,903	1,836	3,564	540	28.3	0.56 b	0.01 a
Corn-04[5] (30.3 ha)	1,646	5,549	5,667	9,147	1,350	24.3	-0.60 c	-0.12 a
Soybean-06[5] (45.3 ha)	2,061	3,741	3,788	5,422	610	16.2	-0.26 c	-0.09 a
Soybean-07[5] (30.0 ha)	2,414	3,852	3,872	5,314	500	13.1	-0.11 c	11.2 a

[1]StDev – Standard deviation.
[2]CV – Coefficient of Variation.
[3]Skewness: (a) symmetric; (b) positive skewness; (c) negative skewness.
[4]Kurtosis: (a) mesokurtic; (b) platykurtic; (c) leptokurtic.
[5]- Normality at 5% probability using Anderson-Darling and Kolmogorovs- Smirnov tests.

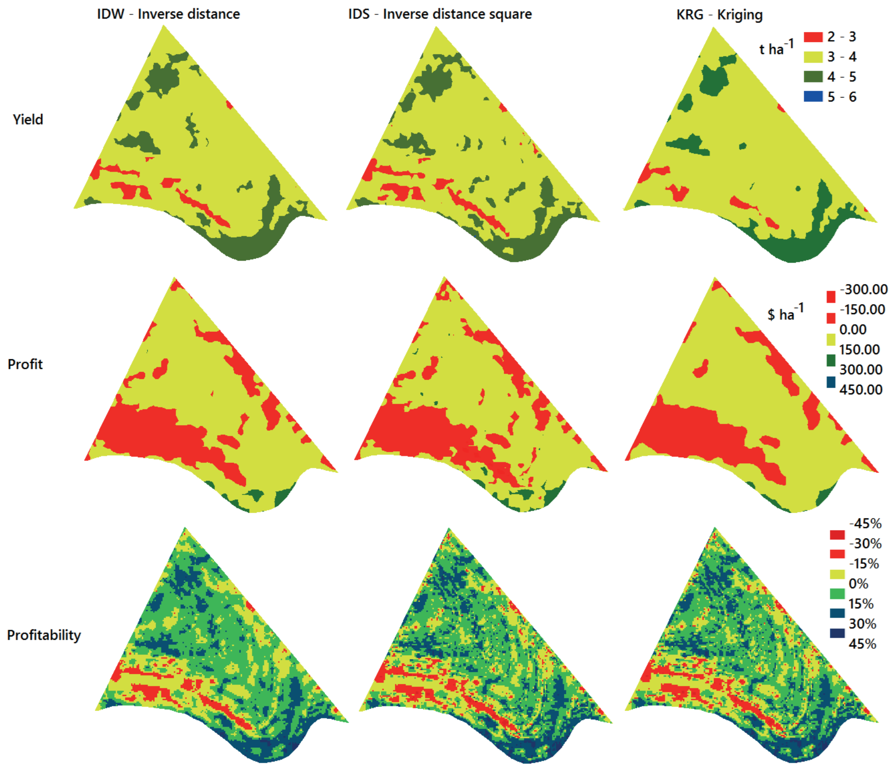


Figure 2. Yield and profit maps for the harvest of Soybean-06 using various interpolation methods: (i) inverse distance weighted (IDW), (ii) inverse distance weighted squared (IDS) and (iii) kriging (KRG). The production cost (Table 1) and sale prices of the product (Table 2 and 3) were used from the month of harvest.

areas, the variability in the data is large, as in the specific case of 15 ha (soybean-03) to 45 ha (soybean-06). However, these CVs were lower than those found by Yang *et al.* (2002) for grain sorghum (from 32 to 57%). Except for soyean-03, the yields were slightly skewed to the left. The yield distributions for corn-04 and soybean-06 were slightly flatter than a normal distribution, whereas the yield distributions for soybean-07 was significantly more peaked than a normal distribution.

In the geostatistical analysis, the cross-validation method indicated an exponential model as the best fit to the semivariogram for yield and profit in all cases. The spatial dependence was moder-

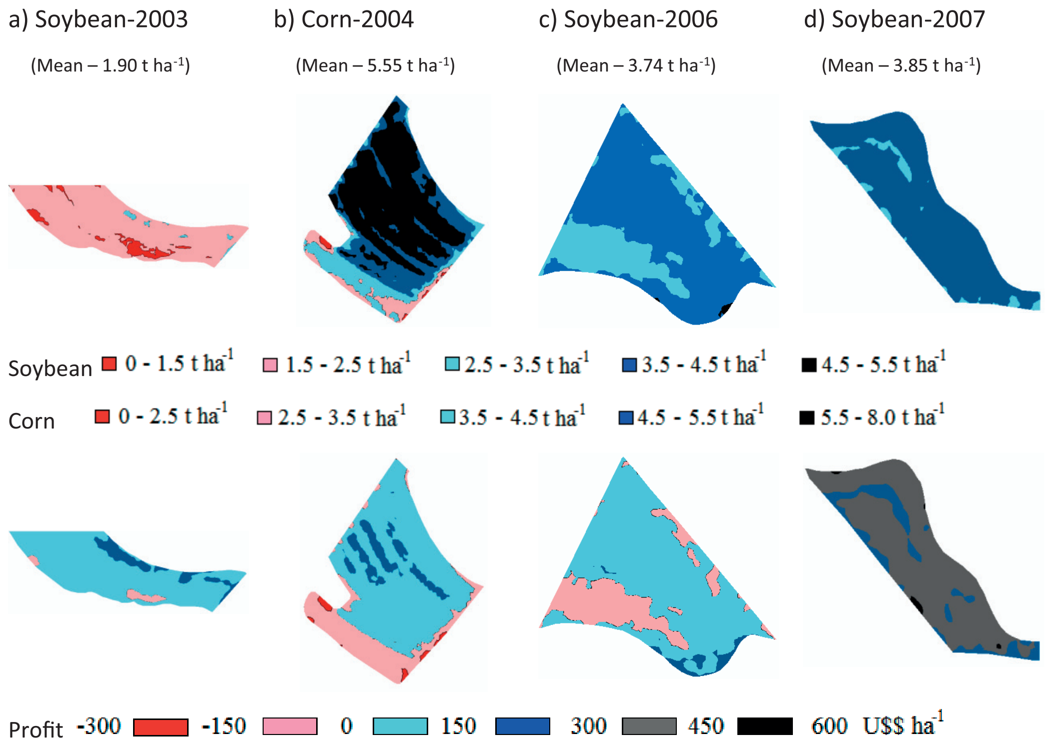


Figure 3. Yield and profit maps for the harvest of Soybean-03 (a), Corn-04 (b), Soybean-06 (c), and Soybean-07 (d) using kriging interpolation.

ate in three cases (Soybean-03, Corn-04, and Soybean-06) and weak for Soybean-07.

A visual comparison of the yield and profit maps (Figure 2) shows that kriging provided better separation among classes. As expected, the shape of the profit maps was strongly impacted by the yield maps (Figures 2 and 3) and reveals the spatial patterns within the fields, agreeing with Yang *et al.* (2002). These profit maps were built with prices right after harvest. Only field 4 (soybean 2007) did not have significant areas where profit was negative (red and pink in Figure 3). The large area with the large negative profit corresponds to the only year with corn.

The best profit year included soybeans in 2007, despite that the mean yield being almost the same as in 2006. The reason for this profit is that the the soybean sales price was US$ 181.83 in 2006 and US$ 232.50 ton^{-1} in 2007, which is evidence that a profit map contributes to more robust decision making than a yield map. Yang *et al.* (2002) states the this within-field yield variability can be attributed to a variety of factors, including soil texture, natural fertility, drainage characteristics, plant water availability, depth of rooting, seedbed quality over short distances and weed infestations, which is why crop yield is considered the most important piece of information in precision agriculture in that it integrates the effects of all of these spatial variables.

The profit for each area was simulated using the three interpolators in a sale scenario that started in the harvest month and ended in the sixth subsequent month (Figures 4 and 5). In all cases, the maximum and minimum values were found for the interpolator IDS, which was the interpolator that had the highest amplitude (less smoothing, Figure 5). Taking into account that profit is directly linked to economic factors and because whether the stowage of products for sales in later months is a good practice is not

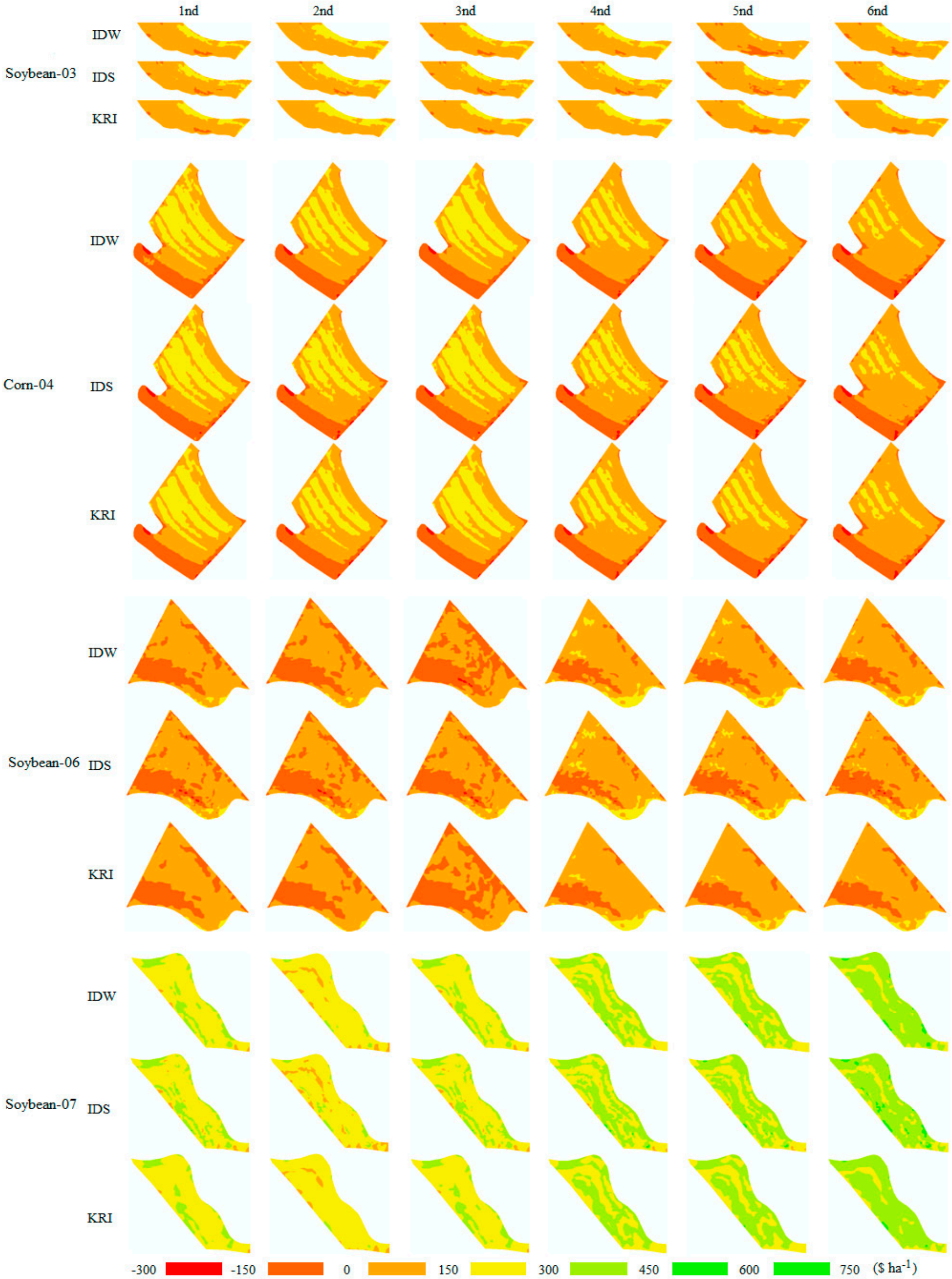
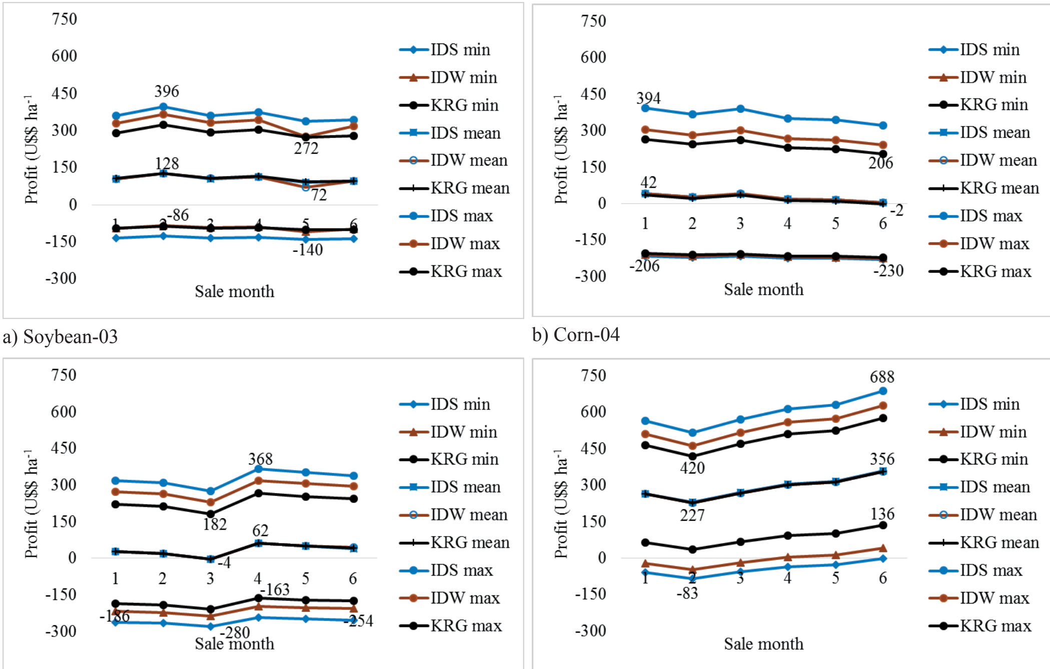


Figure 4. Profit maps for the harvest of Soybean-03 (a), Corn-04 (b), Soybean-06 (c), and Soybean-07 (d) as a function of a six-month sale scenario.

predictable, for all analyzed cases, the immediate sale after the harvest does not generate prejudice, but in some cases, if the crop was stored, the sale would not cover the planting cost.

The profit inside (Figure 5) a field varied from a loss of at least US$ 90 ha^{-1} (soybean 2003), US$ 210 ha^{-1} (corn 2004), and US$ 160 ha^{-1} (soybean 2006), to no loss (soybean 2007), to a gain of at



a) Soybean-03 b) Corn-04

c) Soybean-06 d) Soybean-07

Figure 5. Minimum and maximum profit (US$ ha^{-1}) as a function of a six-month sale scenario based on (i) inverse distance weighted (IDW), (ii) inverse distance weighted squared (IDS) and (iii) kriging (KRG) for the field sites (a) Soybean-03, (b) Corn-04, (c) Soybean-06, and (d) Soybean-07 using yield monitor data.

least US$ 270 ha^{-1} (soybean 2003), US$ 210 ha^{-1} (corn 2004), US$ 180 ha^{-1} (soybean 2006), and US$ 420 ha^{-1} (soybean 2007). All fields showed large profit variations that would not be easily found by analyzing a yield map alone. As suggested by Massey *et al.* (2008), a farmer can determine the areas of the field that were above or below economic benchmarks across years with the aggregation of several years of data for different crops in the same field.

To increase profits, lowering operation costs is probably the most important step (Yang *et al.*, 2002). Because the studied fields already use no-till farming, not much can be done to reduce machinery costs. If a specific area in a field consistently loses money over the years, that area could be switched to forage production or simply left unused. The use of fertilizer could be optimized by site-specific fertilization, if the investment could be paid back in a few years. If a profit map generated with a one-year yield map and the regional costs proves to be a useful decision tool, it is advisable to invest in yield maps for the next several years and to detail the fixed and variable costs so profit inferences will be more realistic.

A shortcoming must be addressed: The final accuracy of a profit map is influenced both by the spatial prediction from the yield map and the quality of the economic data. The goal of this study was to show the high variability of profit data, independent of the precision of the economic data.

In the comparison of the interpolator effect on yield and profit maps, the mean absolute difference (MAD, Table 5) varied on average from 0.06 to 0.20 t ha^{-1} for yield and from 8.62 to US$ 30.23 for profit, always showing the highest differences between the KRG and IDS methods.

The method presented in this paper was useful for converting yield data to profit maps. Yield

Table 5. Mean absolute difference (MAD) for the comparisons between KRG_IDS, KRG_IDW, and IDS_IDW.

MAD		Culture	KRG_IDS (Minimum value)	KRG_IDW	IDS_IDW (Maximum value)
	Yield (t ha^{-1})	Soybean-03	0.146	0.120	0.039
		Corn-04	0.323	0.257	0.093
		Soybean-06	0.172	0.140	0.045
		Soybean-07	0.144	0.123	0.046
		Average	0.20	0.16	0.06
		Culture	KRG_IDS	KRG_IDW	IDS_IDW
	Profit (US$)	Soybean-03	27.54	22.58	7.45
		Corn-04	28.44	22.63	8.18
		Soybean-06	31.36	25.55	8.25
		Soybean-07	33.58	28.52	10.61
		Average	30.23	24.82	8.62

and profit data had moderate (Cambardella *et al*., 1994) spatial dependence in most cases. Profit data were less smoothed by interpolation by the inverse distance weighted squared (IDS) and more by kriging (KRG). The influence of the interpolator type (inverse of distance-IDW, IDS and KRG), used for data interpolation to draw thematic maps was considered small because the mean absolute difference varied between 0.06 and 0.20 t ha^{-1} for yield and between US$8.62 and US$ 30.23 for profit, always showing the highest differences for KRG and IDS. Therefore, the interpolator choice is of secondary importance. Furthermore, all fields showed a large profit variation that would not have easily been found by analyzing a yield map.

Acknowledgements

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Resumen

C.L. Bazzi, E.G. Souza, R. Khosla, M.A. Uribe-Opazo y K. Schenatto. 2015. Mapas de beneficio y de rentabilidad en la agricultura de precisión. Cien. Inv. Agr. 42(3): 385-396. Durante los últimos años, los mapas de rendimiento se han convertido económicamente viables para los agricultores, debido a los avances tecnológicos en la agricultura de precisión. Sin embargo, la evidencia de la rentabilidad del rendimiento, aún es desconocida, y la variabilidad del rendimiento rara vez ha sido correlacionada con la variabilidad de la rentabilidad. A diferencia de los mapas de rendimiento, los mapas de rentabilidad pueden suministrar información adicional relacionada con el retorno económico para cada área particular del campo. El objetivo del presente trabajo ha sido estudiar como las decisiones de gestión pueden ser facilitadas por la transformación de los conjuntos de datos de los mapas del rendimiento en mapas de beneficio, bien como la importancia de la selección de los mapas de interpolación. Para cada conjunto de datos (tres zonas de soya e un de maíz), mapas de rendimiento e de beneficio, fueron generados utilizando los métodos de interpolación de distancia inversa (DI), de distancia cuadrada inversa (DCI) y de Krigagem (KRG). Se puede concluir que los mapas de beneficio y rentabilidad son herramientas importantes para el diagnóstico de la variabilidad espacial del rendimiento económico, ya que ayudan a los agricultores en la gestión de la toma de decisiones. El impacto del tipo de interpolación fue de menos de 200 kg por hectárea en el rendimiento, US$ 30 en el beneficio, significando que la elección puede ser colocada en el segundo plano. En adicción, los mapas de beneficio mostraron una gran variabilidad que no haría fácil encontrar, solamente por el análisis de los mapas de productividad.

Palabras clave: Agricultura de precisión, mapa de beneficio.

References

Birrell, S.J., S.C. Borgelt, and K.A. Sudduth. 1995. Crop yield mapping: Comparison of yield monitors and mapping techniques. p. 15-31. *In*: Site–Specific Management for Agricultural Systems. Madison: ASA; CSSA; SSSA.

Blank, S.C., K.W. Erickson, and C.B. Moss. 2005. Profit Patterns Across American Agriculture. Journal of Agricultural and Resource Economics 30: 205-230.

Cambardella, C.A., T.B. Moorman, J.M. Novak, T.B. Parkin, D.L.Karlen, R.F. Turco, and A.E. Konopka. 1994. Field-scale variability or soil properties in Central lowa Soils. Soil Science SocietyAmerica Journal 58:1501-1511.

Coelho, E.C., E.G. Souza, M.A. Uribe-Opazo, and R.P. Neto. 2009. Influência da densidade amostral e do tipo de interpolador na elaboração de mapas temáticos. Acta Scientiarum 31:165-174.

Jaynes, D.B., and T.S. Colvin. 1997. Spatiotemperal variability of corn and soybean yield. Agronomy Journal 89:30–37.

Jones, N.L., R.J. Davis, and W. Sabbah. 2003. A comparison of three-dimensional interpolation techniques for plume characterization. Ground Water 41:411-419.

Jones, T.A. 1969. Skewness and kurtosis as criteria of normality in observed frequency distributions. Journal Sedimentary Petrology. Northeast Georgia 39:1622-1627.

Khosla, R., and B. Flynn. 2008. Book Chapter. Understanding and Cleaning Yield Monitor Data. *In*: S. Logsdon (ed.). Soil Science: A Step-by-step Analysis. Amer. Soc. Agron. Madison. WI. USA.

Kravchenko, A.N., G.P. Robertson, K.D. Thelen, and R.R. Harwood. 2005. Management, topographical, and weather effects on spatialvariability of crop grain yields. Agron. J. 97:514–523.

Marinoni O, G.J. Navarro, S. Marvanek, D. Prestwidge, D. Clifford, and L. Laredo. 2012. Development of a system to produce maps of agricultural profit on a continental scale: An example for Australia. Agricultural Systems 105: 33-45.

Massey, E.R., D.B. Myers, N.R. Kitchen, and K.A. Sudduth. 2008. Profitability maps as an input for site-specific management decision making. Agronomy Journal 100:52-59.

Murphy, D.P., E. Schnug, and S. Haneklaus. 1995. Yield mapping: A guide to improved techniques and strategies. *In*: Site–Specific Management for Agricultural Systems. Madison: ASA; CSSA; SSSA. p. 33-47.

Ping, J.L., and A. Dobermann. 2005. Processing of yield map data. Precision Agriculture 6:193-212.

SEAB/PR-Secretaria da Agricultura e do Abastecimento do Paraná. 2015. Available online at: http://www.agricultura.pr.gov.br/ (Website accessed: March 17, 2015).

Swinton, S.M., and J. Lowenberg-Deboer. 1998. Evaluating the profitability of site-specific farming. Journal of Production Agriculture 11:439-446.

Wollenhaupt, N.C., and R.P. Wolkowski. 1994. Grid soil sampling. Better crops with plant food. Norcross 78(4):6-9.

Yang, C., C.L. Peterson, G.J. Shropshire, and T. Otawa. 1998. Spatial variability of field topography and wheat yield in the Palouse region of the Pacific Northwest. Transactions of the ASAE 41:17–27.

Yang, C., J.H. Everitt, and J.R.C. Robinson. 2002. Spacial variability in yields e profits within ten grain sorghum fields in south Texas. Transactions of the ASAE 45:897-906.