Ciências Agrárias
SEMINA

DOI: 10.5433/1679-0359.2023v44n3p1001

Methodology for estimating productive potential zones from productivity data

Metodologia para estimativa de zonas de potencial produtivo a partir de dados de produtividade

Lara Marie Guanais Santos[1]*; Otávio Jorge Grigoli Abi Saab[2]; Maria de Fátima Guimarães[2]; Ricardo Ralisch[2]; Hevandro Colonhese Delalibera[3]

Highlights

Analysis and interpretation of data from the harvest monitor.
Proposed method for processing and interpreting collection data.
The method was efficient and easy to implement and generated summarized information.

Abstract

The methodology proposed herein for identifying potentially productive zones from yield data captured by harvester onboard sensors aims to establish a viable and easy-to-implement method for defining management zones by running statistical procedures on data from the harvest monitor. To do this, yield data from maize (2018 winter/second growing season) and soybean (2019 growing season) were converted into z-score values and compared at a 99.8% confidence interval of standard normal distribution z. Simultaneously, the degree of linearity was evaluated and Jackknife resampling, for removing data outside the range (outliers) established by the z table (<-3.09 and >3.09). Next, yield z-score algebraic mapping was performed to obtain a mean crop map, then applying three classes from the probability intervals of a plus and minus deviation, resulting in a map of potentially productive zones (below average, average and above average yield). Using this method, 5.72% of the area exhibited low yield potential, 90.71% average potential and 3.57% high yield potential. This analysis method was easy and quick to perform and provided summarized information, facilitating additional field surveys and providing a basis for decision-making.

Key words: Data analysis. Harvest map. Harvest monitor. Map algebra.

[1] Student of the Doctoral Course of the Graduate Program in Agronomy, Universidade Estadual de Londrina, UEL, Londrina, PR, Brazil. E-mail: laramarieguanais@gmail.com
[2] Profs. Drs., Graduate Program in Agronomy, UEL, Londrina, PR, Brazil. E-mail: otavioabisaab@gmail.com; mfatima@uel.br; ricardoralisch@gmail.com
[3] Researcher Dr. from the Agricultural Engineering and Digital Technologies Area, Instituto de Desenvolvimento Rural do Paraná IAPAR-Emater, IDR-Paraná, Londrina, PR, Brazil. E-mail: hevandro@idr.pr.gov.br
* Author for correspondence

Received: Mar. 07, 2022 Approved: June 29, 2023

Resumo

A proposta desta metodologia para estimativa de zonas de potencial produtivo a partir de dados de produtividade obtidos por sensores instalados em colhedoras, tem como objetivo estabelecer um método viável e de fácil execução para a definição de zonas de manejo, empregando procedimentos estatísticos em dados obtidos por monitor de colheita. Para tanto, foram utilizados dados de produtividade das culturas de milho (inverno/safrinha 2018) e soja (safra 2019) convertidos em escore-z e comparados com o intervalo de confiança de 99,8% da distribuição normal padrão z. Simultaneamente, foi avaliado o grau de linearidade e o método Jackknife, removendo-se os dados fora do intervalo estabelecido pela tabela z (<-3,09 e >3,09). Após este procedimento, foi realizado a álgebra dos mapas de escore-z de produtividade para obtenção de um mapa médio das culturas, no qual se aplicou três classes a partir dos intervalos de probabilidade de um desvio para mais e para menos, resultando no mapa de zonas de potencial produtivo em três áreas, abaixo da média, na média, e acima da média de produtividade. Com a aplicação do método, obteve-se 5,72% da área com baixo potencial produtivo, 90,71% com potencial médio e, 3,57% com alto potencial produtivo. Este método de análise demonstrou-se de fácil e rápida execução e proporcionou informação resumida, facilitando ações complementares de levantamento à campo e tomadas de decisão.

Palavras-chave: Análises de dados. Álgebra de mapas. Mapa de colheita. Monitor de colheita.

Introduction

Precision Agriculture (PA) is an integrated management system that aims to improve agricultural activity based on the spatial and temporal variability of crops (Ministério da Agricultura, Pecuária e Abastecimento [MAPA], 2009). This concept, widely applied with the development of computing and embedded electronics, allowed farmers to observe the relationship between soil variations and crop yield. According to Pedersen and Lind (2017), and Souza et al. (2016), it is the result of a number of several factors, such as soil properties and characteristics, use of fertilizers, topographical attributes, climatic conditions and the occurrence of pests and diseases.

When dealing with this spatial variability, the most common approach involves subdividing the area into similar plots, referred to as differentiated management units (DMU) or management zones, based on predetermined characteristics or attributes obtained by collecting soil samples in order to apply localized treatment and improving performance (Speranza et al., 2022; Maldaner et al., 2019).

The aim of subdividing areas into DMUs is to cut input costs and this can be achieved by collecting soil based on a georeferenced grid, or generating theme-based maps from geostatistics. These methodologies help farmers and technical assistance teams to detect the dynamics of the crop's spatial variability and thereby estimate localized input application, minimizing the possibility of applying too much or too little. Inferences can be made regarding the results and observed variability in the field and amendments proposed according to localized soil conditions and plant variability (Richart et al., 2016) in order to boost crop yield (Camicia et al., 2018) and profitability (Carneiro et al., 2016).

The use of harvest maps generated by harvest monitors onboard grain combine harvesters is considered one of the best ways of detecting variability in the field and proposing management initiatives, since it is based on the crop's response to the management and production environment and high sampling rates are achieved at low cost. However, errors can occur in data collection by harvester sensors, and these errors must be eliminated to obtain more reliable maps. Nonetheless, current methodologies are heavily dependent on the skill of the analyst. They are not easily applied to the data generated and are difficult to run on the data from the harvest monitors and obtain a summarized map of management zones or DMUs (Menegatti & Molin, 2004; Michelan et al., 2007; Delalibera, et al., 2012; Souza et al., 2016; Pedersen & Lind, 2017).

Thus, the aim of this study was to establish a viable and easy-to-implement method for defining management zones, using established statistical procedures in order to analyze crop yield data collected by harvest monitor.

Material and Methods

With the aim of establishing a viable, easy-to-implement method for defining management zones based on crop yield data from a harvest monitor, data obtained from maize (2018) and soybean (2019) second crops were used for the purpose of this study. The aim of this methodology is to thoroughly analyze yield data output by harvest monitors, discarding data that do not statistically belong to the population, facilitating the generation of algebraic yield maps for different crops and creating a summarized map of management zones, based on historical information on crop yield in a given agricultural area.

The data was sourced from an agricultural area of 17 hectares under the no-till management system (NTS), in clayey textured Distroferric Red Latosol soil (Santos et al., 2018) in the municipality of Cambé - Parana State, Brazil (23° 8′ 29.99″ S, 51° 20′ 48.51″ W), at an elevation of 521 m. The climate is classified as Cfa - Subtropical with hot summers (Köppen, 1931).

Data were obtained using a John Deere grain combine harvester, model STS 9750, fitted with an impact plate grain yield sensor, *Hall,* effect sensor on the drive wheels, gyroscopic tilt sensor and a GS4® John Deere monitor that displays and records information and outputs data in spreadsheet format.

Data obtained by the yield monitor is initially scanned to remove zeroed and null data, for which purpose a script was developed using Rstudio software. The moisture content for the yield data collectors was also standardized at 13% using the method proposed by Aguiar (1977). Next, using Excel 2010 *spreadsheet software,* Standard Deviations were analyzed according to standard normal distribution z in order to transform each yield reading into kg ha^{-1}, assigning a z-score index with a zero mean and standard deviation equal to one, so that it could be later compared with a content interval of 99.8% of standard normal distribution z derived from convergence theorems, where values outside the content interval from -3.09 to 3.09, were considered not to belong to the population (Harter, 1960), i.e. values not considered to belong to the population of the set were removed, as proposed in the Jackknife method (Wu, 1986).

Thus, the process must begin by removing the outliers of z-score indices in order to recalculate the indices on each removal, since they can move inside or outside the interval based on variations in the central tendency and dispersion measurements (Delalibera et al., 2017).

Eq 1. $$Z = \frac{X_i - \overline{X_i}}{\sigma}$$

Where,

x_i – *One-off sample (yield)*

$\overline{x_i}$ – *Dataset mean (yield)*

σ – *Dataset standard deviation*

In addition to applying *Jackknife* resampling, it is important to evaluate the degree of linearity of the ordered frequency of indices, z-score, for each harvest map, which is easily obtained by ordering z-score from lowest to highest and applying a scatter plot to fit the linear equation, where the degree of linearity is represented by the r^2 of the data fit to a straight line (Delalibera et al., 2017).

This procedure for verifying the degree of linearity of the ordered frequency of z-score is similar to the mathematics of some tests for verifying the degree of significance of the fit to data normality, such as Lilliefors and Anderson-Darling. However, the aforementioned methods cannot be applied because the size of the dataset is incompatible with the test rules.

It is advisable to evaluate the degree of linearity of the ordered frequency of z-score and also the application of the *Jackknife* method to z, since methods of comparison with theoretical distributions may be affected by low sensitivity when applied directly to very large datasets with high variability and dispersion, in which case the application of z alone does not detect outliers. However, the evaluated set may not exhibit the linearity of the ordered frequency of its deviations.

The intention is always to fit the set to a normal distribution, where the closer r^2 is to 1.0, the greater the degree of linearity of the ordered frequency of z-score and, consequently, there is a better tendency to fit a normal distribution, reflected in the representativeness of its measurements of central tendency and dispersion. Linearity equal to or greater than 0.80 can be considered representative (Delalibera et al., 2017; Wu, 1986; Hair et al., 2009; Lentner & Bishop, 1993).

After preliminary analysis to remove null data and data not belonging to the population, with the respective standardization of yield data z-score, these variables were represented two-dimensionally in index maps of z-score for soybean and maize crop yields by interpolation using Triangulated Irregular Networks (TIN), but not intended to estimate data in the spaces between points, nor to smooth the network variation steps, since accepted statistical methods for removing non-representative values from the sets were applied, and therefore interpolations that implement smoothing and/or value estimation could lead to representativeness errors. The TIN method uses a smaller number of neighboring points to calculate the interpolation, maintaining the level of accuracy of a denser regular grid, rendering the result more consistent with the input grid data (Mikhail et al., 2001).

Yield maps acquired by a harvest monitor provide a high density of points sampled per unit area and it is considered that removing up to 50% of the data does not justify the need to apply estimation methods to cover empty spaces, since area size is considered irrelevant. The maps plotted on the basis of yield z-score were generated using GIS QGIS 3.4.6. software.

Once the mapped z-score values had been obtained for each crop, a map algebra was applied to compare the soybean and maize maps with the aim of obtaining a means map averaging the yield z-score. In statistical terms, this procedure allows for dilution of the effects of uncontrolled factors, obtaining summarized information for facilitating the interpretation of the combined information as a basis for more assertive decision-making.

Subdividing this final averages map of the area into management zones involved applying a statistical parameter resulting in only three subdivisions, aimed at facilitating interpretation. To do this, one plus and one minus Standard Deviations from the mean were taken into account, classifying the map into three zones (potentially productive zones). The map zones with a z-score deviation lower than -1 were considered to have a low index of yield potential; zones with a z-score value between -0.999 to 0.999 were considered of average normal potential, and areas with a deviation higher than 1 were considered to have a high index of yield potential.

In this procedure, based on perfect normal distribution, 68.26% of occurrences were concentrated in the graph area demarcated by one standard deviation to the right and one standard deviation to the left of the mean, and what remains is 15.77% on each side of the distribution (99,8% of the interval contained in the distribution of z). This percentage of distribution does not necessarily occur in a measured phenomenon, but in this case the data included in each defined interval (≤-1; -0.999 to 0.999 and ≥1 deviation) were considered to correspond to statistically different levels of yield potential below average, average, and above average, respectively.

After mapping the historical average of potentially productive zones, QGIS software was used to extract the yield histograms of z-score providing the area of each zone formed, in addition to the frequency distribution, in order to evaluate the behavior of the yield potential of the area. During descriptive analysis of the data, the Coefficient of Variation (CV%) was calculated by adding a constant of one to the values with the aim of obtaining a more representative index fit (Hair et al., 2009).

Results and Discussion

By applying the *Jackknife* method using the value of z and verifying the degree of linearity of the ordered frequency of z-score, it was possible to verify the best fit for the yield distribution data (Figure 1). Figures 1F and 1H show that the outliers are responsible for the change in direction at the ends of the ordered frequency distribution of z-score, resulting in a poor linearity fit. Therefore, discrepant data were removed, starting with the value of z-score furthest from the mean of standard distribution for the set.

The importance of verifying the degree of linearity of the ordered frequency for yield (z-score) is shown by the histograms in Figures 1C and 1D and in the ordered frequency diagrams in Figures 1H and 1I. This is because the low sensitivity of z when identifying data not belonging to the population during application of *Jackknife* resampling to very large dispersed datasets is explicit, which means that it is essential to evaluate the linearity of the responses of z-score values for this type of measured event. Therefore, in this data filtering procedure, the *Jackknife* method alone based on z values does not initially identify outliers. However, subsequently applying the ordered frequency diagram of z-score reveals a low degree of linearity (Figure 1H), which, by excluding discrepant data from the right (positive) end of the diagram, means that the *Jackknife* begins to identify data that do not belong to the population, since there is a reduction in the dispersion measurements for the dataset. In this case, outliers were removed until the degree of linearity of the ordered frequency of z-score reached an r^2 greater than 0.80 and there were no more indices outside the content interval applied, (Figure 1I).

Figure 1 also shows an improvement in the behavior of the dataset in the corresponding distribution histograms, with a better fit to normality and, consequently, improved representativeness for the dispersion measurements and the central tendency of the event. According to Mirshawka (1986), z-score values outside the ±3.09 range represent data not belonging to the population tested in relation to the distribution of z. Samohyl (2005) points out that these discrepant data items in evaluations of agricultural events may be related to factors such as labor, machinery, raw material, environment and the measurement method. Factors related to machinery include harvesting with half a platform or closing off some areas, sensor read errors and other factors that are normal and often systematic during the harvesting process. These factors should not necessarily be excluded, since they are part of the mechanized harvesting process and therefore affect dilution when applying algebraic mapping in order to generate the historical average map of potentially productive zones.

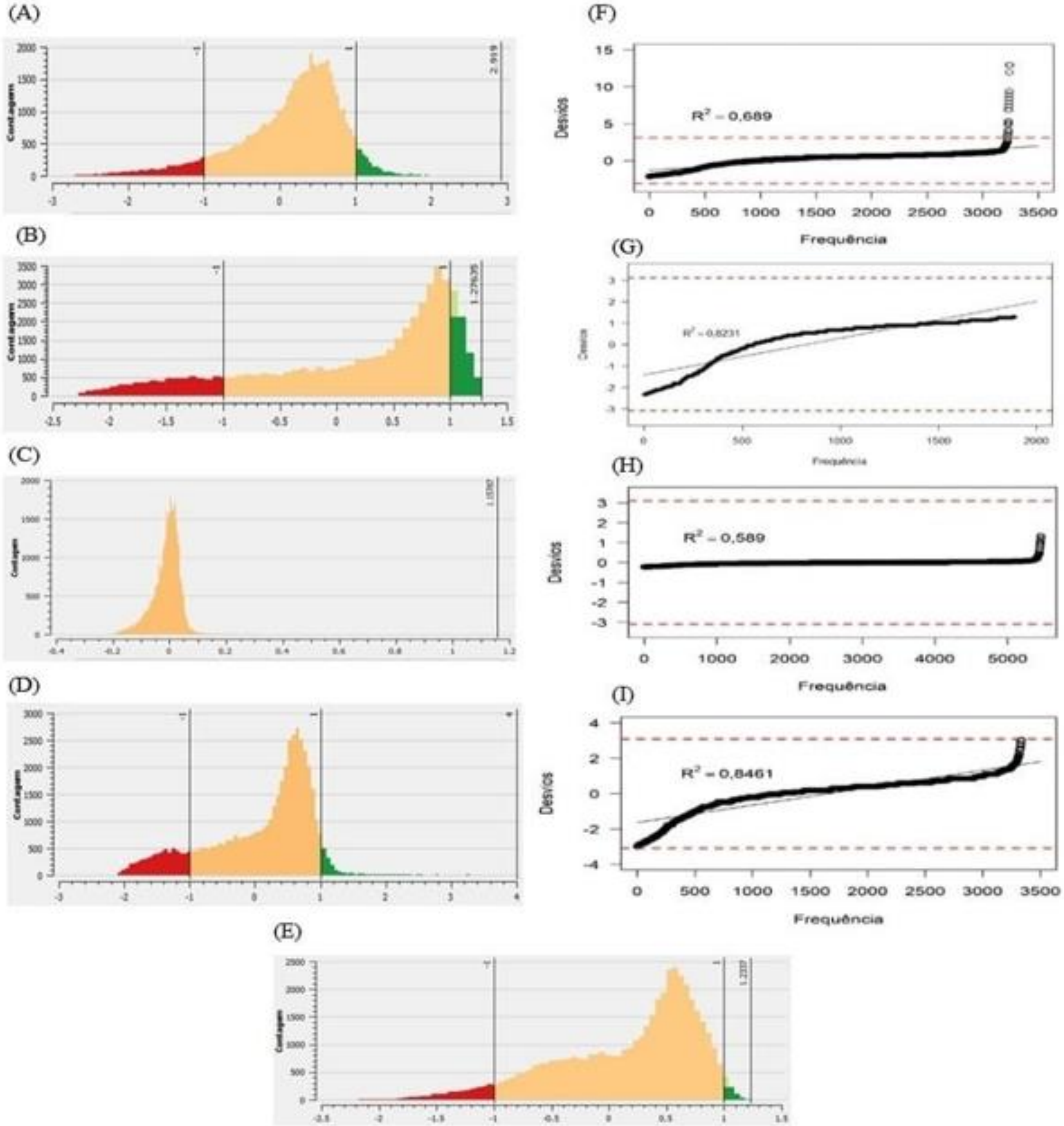

Figure 1. Frequency histograms of yield z-score and ordered frequency diagram of z-score with the respective linearity fits, where: Fig. 1A and 1F show the behavior of the z-score for maize without applying the *Jackknife* method, Figs. 1B and 1G behavior of z-score for maize when the *Jackknife* method, Fig. 1C and 1H behavior of z-score for soy when the *Jackknife* method, Fig. 1D and 1I behavior of z-score for soybean with the *Jackknife* method, Fig. 1E relates to the behavior resulting from averaging the maps of z-score for maize (Fig. 1B/1G) and soybean (Fig. 1D/1I). Where: values below -1 for z-score are shown in red and represent zones of low yield; values between -0.999 to 0.999 for z-score are shown in yellow and represent zones of average normal yield potential; and values above 1 for z-score are shown in green and represent areas of high yield potential.

A study undertaken by Delalibera et al. (2017), who used experimental data analysis methods to evaluate bean grain losses on header during mechanized harvesting, concluded that the application of the Jackknife method based on z during preliminary data analysis afforded advantages, such as improved quality, representativeness and reliability of the information obtained for subsequent analyses, since fitting to an appropriate theoretical distribution for events exhibiting considerable dispersion allows for the careful exclusion of non-discrepant samples, without impairing the representativeness of the results and therefore reflecting the reality of the event.

During algebraic mapping (see histogram in Figure 1E), the effects of uncontrolled random variables on the yield variable is verified. Uncontrolled random events include variables such as climate, pests, diseases and even the effects of different cultivars of the same crop and during the same season. In addition, the frequency distribution histograms exhibit asymmetric behavior on the right, indicating a trend in this area towards increased yield, since stability would be represented by a bell curve perfectly aligned with the center of distribution, i.e. it can be inferred that the management methods applied to the area are boosting yield.

This fact (see Figure 1B) in regard to maize cultivation, leads to the conclusion that investments made in maize farming are boosting yield. This is less evident in the soybean crop (Figure 1D), where the top of distribution is closer to the center (mean/zero), with a tendency towards stabilization of the area's yield potential and, therefore, new or additional investments in management will not result in a significant increase in yield. It is worth mentioning that maize tends to respond faster to management practices, and some soybean cultivars are more tolerant to variations in soil fertility and may not respond with increased yield in years with favorable weather conditions.

Figure 1E shows that there is an increase in the average yield potential of the area as time progresses, based on current management methods, evidenced by the asymmetry on the right of the histogram for zones of average yield potential. Note that, as these data are ongoing, if there are cases of histograms with binomial or multinomial representation or distribution for yield z-score for a given area, this indicates that we are dealing with different populations that must be evaluated separately, as in the case of this study of maize and soybeans, maintaining the algebraic mapping situation at the end of analysis.

According to Blackmore (2003) and Lark et al. (1999) history data over several seasons of planting different crops is necessary to identify and propose management zones associated with soil characteristics, which is true and valid for the purpose of this study.

Even so, based on what is stated herein, it is possible to carry out a combined analysis of data from different sources (crops and agricultural years), since the conversion of yield to z-score and comparison with the distribution of z values allows scaling or standardization of the different quantities relating to the different crop yields for the same scale within a content interval from -3.09 to 3.09, facilitating comparison and/or algebraic mapping without loss of the variability information intrinsic to the dataset.

This effect can be seen in Figure 2E, which represents the mean map of z-score for yield in Figures 2C (maize) and 2D (soybean), summarizing information from different sources in a single average map of potentially productive zones in the area, which is not possible for yield data expressed in grams, as can be seen in Figure 3. This is because different crops respond within different intervals and values of magnitude in regard to the means for dispersion and central tendency, where maize yield can be considered low, but not soybean yield. However, the behavior of intrinsic variabilities is not necessarily expressed in this way after standardization, as proposed herein. This effect is illustrated in Table 1. After conversion into z-scores, both crops exhibit zeroed means and a standard deviation of one.

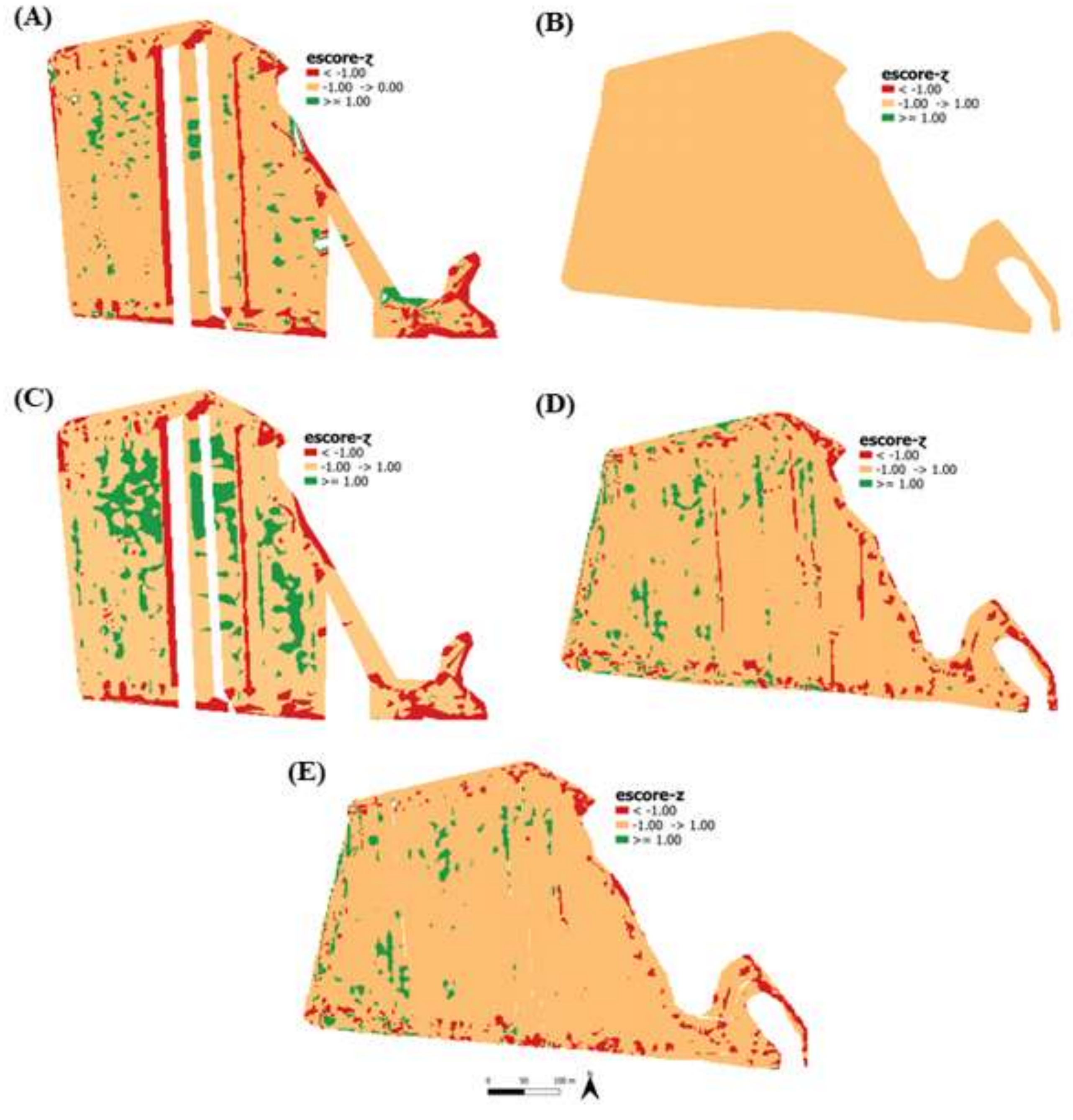

Figure 2. Maps of management zones derived from the z-score for crop yields, classified into three potentially productive zones by the mean standard deviation method, where: Fig. 2A is the map of z-score for maize with no *Jackknife*, Fig. 2B, the map of z score for soy without Jackknife, Fig. 2C, the map of z-score for maize with *Jackknife*, Fig. 2D, the map of z-score for soybeans with *Jackknife*, Fig. 2E, the averages map for potentially productive zones, resulting from algebraic mapping of Fig 2C (maize) and Fig. 2D (soybean). Where: values below -1 z-score are shown in red and represent areas of low yield potential; values between -0.999 to 0.999 for z-score are shown in yellow and represent zones of normal average yield potential; values above 1 z-score are shown in green and represent areas of high yield potential.

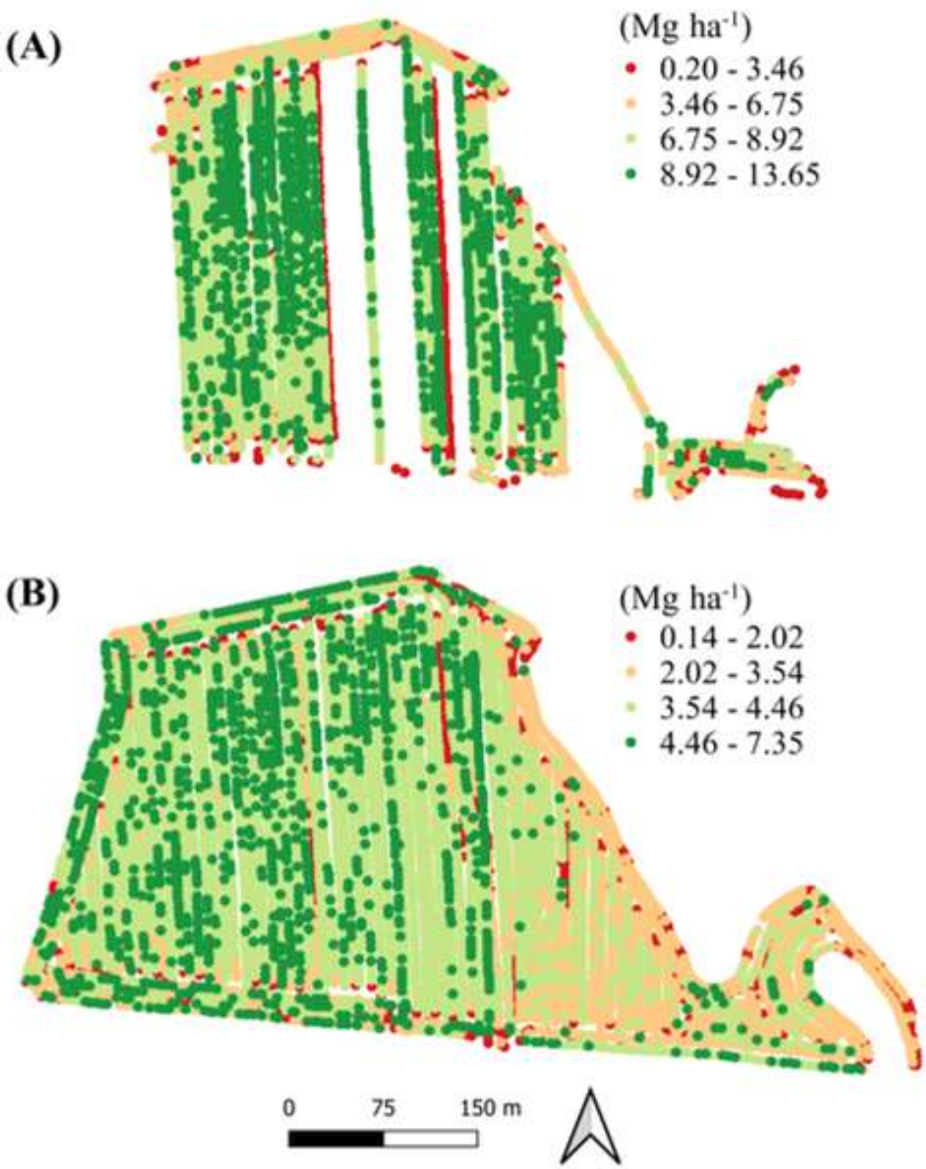

Figure 3. Representation of yield data (Mg ha^{-1}) without prior data processing and color-coded according to the software default values. Where: Fig. 3A relates to the maize crop and Fig. 3B relates to the soybean crop.

Table 1
Descriptive analysis of data sets from the harvest monitor

Descriptive analysis	Maize				Soybean			
	DB (Mg ha^{-1})	z-score	CT (Mg ha^{-1})	ezJL	DB (Mg ha^{-1})	z-score	CT (Mg ha^{-1})	ezJL
Mean yield	6.86	0.00	6.76	0.00	4.09	0.00	3.75	0.00
Standard error	40.96	0.01	35.80	0.02	230.10	0.01	15.04	0.02
Median	7.48	0.20	7.48	0.30	3.93	-0.01	3.93	0.19
Mode	8.81	0.62	8.81	0.89	4.72	0.03	4.72	0.19
Standard deviation	3124.72	1.00	2718.08	1.00	18055.48	1.00	1171.67	1.00
Sample variance	9763.88	1.00	7387.95	1.00	326000.37	1.00	1372.80	1.00
Kurtosis	19.64	19.64	-0.29	-0.44	6024.11	6024.11	1.31	1.14
Asymmetry	1.57	1.57	-0.72	-0.82	77.21	77.21	-0.93	-0.98
Interval	47.12	15.08	13.52	3.66	1412.77	78.25	7.21	6.02
Minimum	0.12	-2.16	0.12	-2.38	0.14	-0.22	0.14	-2.98
Maximum	47.24	12.92	13.64	1.28	1412.91	78.03	7.35	3.04
Count	5821.00	5821.00	3442.00	3442.00	6157.00	6157.00	3756.00	3756.00
CV (%)	45.49	87.89	40.20	86.04	440.64	107.78	31.18	102.03

RD – Raw data from the harvest monitor; z-score – ***z**-score* of yield; ezJL – z-score with *Jackknife* and verification of the degree of linearity of the ordered frequency for ***z*-score**; PD - Processed data.

Table 2 shows the effect of processing the data, resulting in an increase in the areas of low and high yield potential, with a consequent drop in the zone of mean normal potential. This effect is more evident in the soybean maps, prior to data processing (Figure 2B), with an apparently homogeneous area and the absence of zones of low and high yield potential. After processing (Figure 2D), these plots were differentiated.

Table 2
Area of potentially productive zones (in hectares and as a percentage), color-coded on maps

Figure/Maps	Area (ha)					
	Red	(%)	Yellow	(%)	Green	(%)
2A/**ez** Maize	1.50	13.16	9.34	82.10	0.54	4.74
2C/**ez**JL Maize	1.61	14.03	8.24	71.93	1.61	14.04
2B/**ez** Soybean	-	-	17.21	100.00	-	-
2D/**ez**JL Soybean	1.28	7.46	15.03	87.40	0.88	5.14
2E/Mean of **ezJL** Maize and Soybean.	0.99	5.72	15.67	90.71	0.62	3.57

Red - Zones with low yield potential; Yellow - Normal average potentially productive zones; Green - Zones with high yield potential; ez - z-score yield data; ezJL - z-score with *Jackknife* and verification of the degree of linearity of the ordered frequency of z-score.

The application of data processing using established statistical concepts suitable for large datasets, such as z values and exclusion of discrepant data by the *Jackknife* method together with the evaluation of the degree of linearity of the ordered frequency of z-score values, significantly affects the quality of the information generated, as shown in Figure 2 and Table 1. Table 1 also shows that, in the count variation source, data processing removed 40.8 and 38.9% of the data from the sets for maize and soybeans respectively. Due to the high density of sampled values per area unit, it is assumed that the information generated was not impaired, and that the high coefficient of variation for both crops is a characteristic of the yield variable during mechanized grain harvesting.

In addition, the information extracted from the yield maps is considered by several authors as one of the best variables for detecting variability in the field and proposing management methods, since in addition to representing the crop response to management methods and the production environment, this variable is obtained at low cost and with a high sampling rate (Pedersen & Lind, 2017; Souza et al., 2016; Menegatti & Molin, 2004).

Note that the proposed methodology was considered easy to implement, since it involves three steps executed by simple and robust statistical methods. The first step is removal of discrepant data, the second relates to algebraic mapping and the third to the subdivision of the area into potentially productive zones. Carrying out these three steps requires basic knowledge of electronic spreadsheet manipulation to calculate standard deviations, means, divisions and subtractions, fixed critical values for data exclusion and degree of linearity, and basic knowledge of geographic information systems not requiring in-depth knowledge for interpretation. Therefore, these steps can be correctly performed by a trained technician, or automatically if dedicated software is written for this purpose.

It is also assumed that a larger set of crop/yield maps for the same area is available, in which case the representativeness of the average map of potentially productive zones will be greater, given the dilution of uncontrolled effects on the dataset and highlighting soil variables that influence crop yield. However, it is still advisable, as a continuation of this work, that studies be conducted to survey soil variables in the field, based on the potentially productive zones obtained, with the aim of correlating them with the proposed management zones, since in some cases soil variables are easier to handle.

Conclusion

The application of analysis methods to data acquired from harvest monitors proposed herein consists of only three steps, based on robust and easy-to-implement statistical methods.

The method used to remove non-representative data from the set has proven to be viable for data from yield monitors on board grain combine harvesters.

The algebraic mapping method for different crops has proven to be efficient and did not impair the quality of the information generated.

The method used for the subdividing the area into management zones was adequate and the number of classes sufficient for summarizing the information, facilitating complementary initiatives such as carrying out surveys and collecting variables in the field, especially those related to the soil, obviating the need for gridded soil sampling.

Acknowledgments

We would like to express our thanks to the Coordination for the Improvement of Higher Education Personnel (CAPES) for the scholarship, the Rural Development Institute of Paraná IAPAR-Emater (IDR-Paraná), Agricultural Engineering and Digital Technologies division for providing the methodology presented in this study, the Agricultural Telemetry company Agritel, and Mr. Ademir Inocente, owner of the study area.

References

Aguiar, P. A. A. (1977). *Padronização da umidade dos grãos na experimentação agrícola.*

Blackmore, S. (2003). Consciousness in meme machines. *Journal of Consciousness Studies, 10*(4-5), 19-30.

Camicia, R. G. M., Maggi, M. F., Souza, E. G., Bazzi, C. L., Konopatzki, E. A., Michelon, G. K., & Pinheiro, J. B. S. (2018). Productivity of soybean in management zones with application of different sowing densities. *Ciência Rural, 48*(12), 1-9. doi: 10.1590/0103-8478cr20180532

Carneiro, J. S. S., Santos, A. C. M., Fidelis, R. R., Silva, S. P., Neto, Santos, A. C., & Silva, R. R. (2016). Diagnóstico e manejo da variabilidade espacial da fertilidade do solo no cerrado do Piauí. *Revista de Ciências Agroambientais, 14*(2), 1-11. doi: 10.5327/rcaa.v14i2.1469

Delalibera, H. C., Higashibara, L., & Ralisch, R. (2017). Estimativa de perdas na colheita mecanizada de grãos: adequação da metodologia para plataformas universais modernas. *Anais do Congresso Brasileiro de Engenharia Agrícola - CONBEA,* Maceió, AL, Brasil, 46.

Delalibera, H. C., Weirich, P. H., Neto, & Nagata, N. (2012). Management zones in agriculture acording to the soil and landscape variables. *Engenharia Agrícola, 32*(6), 1197-1204. doi: 10.1590/S0100-69162012000600021

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2009). *Análise multivariada de dados.* Bookman Editora.

Harter, H. L. (1960). Tabelas de alcance e alcance estudantil. *The Annals of Mathematical Statistics, 31*(4), 1122-1147.

Köppen, W. P. (1931). *Grundriss der klimakunde.* Walter de Gruyter.

Lark, R. M., Bolam, H. C., Mayr, T., Bradley, R. I., Burton, R. G. O., & Dampney, P. M. R. (1999). Analysis of yield maps in support of field investigation of soil variation. In *European conference on precision agriculture,* Odense, Dinamarca.

Lentner, M., & Bishop, T. (1993). *Experimental design and analysis* (2nd ed.). Valley Book Company.

Maldaner, L. F., Wei, M. C. F., & Molin, J. P. (2019). *Mapas de produtividade.* (Boletim Técnico, 4). USP-ESALQ.

Menegatti, L. A., & Molin, J. P. (2004). Remoção de erros em mapas de produtividade via filtragem de dados brutos. *Revista Brasileira de Engenharia Agrícola e Ambiental, 8*(1), 126-134. doi: 10.1590/S1415-43662004000100019

Michelan, R., Souza, E. G. de, & Uribe-Opazo, M. A. (2007). Determinação e remoção do tempo de atraso em mapas de colheita de milho. *Acta Scientiarum. Agronomy, 29*(2), 147-155. doi: 10.4025/actasciagron.v29i2.337

Mikhail, E. M., Bethel, J. S., & McGlone, J. C. (2001). *Introdução à fotogrametria moderna.*

Ministério da Agricultura, Pecuária e Abastecimento (2009). *Agricultura de precisão.* (Boletim Técnico). MAPA.

Mirshawka, V. (1986). *Controle da qualidade industrial.* Ed. CDQI.

Pedersen, S. M., & Lind, K. M. (2017). *Precision agriculture: technology and economic perspectives.* Cham: Springer International Publishing.

Richart, A., Piccin, A. L. L., Konopatzki, M. R. S., Kaefer, K. A. C., Moratelli, G., Kaefer, J. E., & Ecco, M. (2016). Análise espaço-temporal de atributos químicos do solo influenciados pela aplicação de calcário de cloreto de potássio em taxa variável. *Scientia Agraria Paranaensis, 15*(4), 391-400. doi: 10.18188/sap.v15i4.12260

Samohyl, R. W. (2005). Controle estatístico de processo e ferramentas da qualidade. *Gestão da qualidade: teoria e casos.* Rio de Janeiro: Elsevier, 261-269.

Santos, H. G., Jacomine, P. K. T., Anjos, L. H. C. dos, Oliveira, V. A. de, Lumbreras, J. F., Coelho, M. R., Almeida, J. A., Cunha, T. J. F. (2018). *Sistema brasileiro de classificação de solos.* EMBRAPA.

Souza, E. G., Bazzi, C. L., Khosla, R., Uribe-Opazo, M. A., & Reich, R. M. (2016). O tipo de interpolação e o cálculo de dados de mapas de rendimento de culturas são importantes para a produção de culturas de precisão. *Journal of Plant Nutrition, 39*(4), 531-538. doi: 10.1080/01904167.2015.1124893

Speranza, E. A., Olim, G. E. de S., Inamasu, R. Y., Vaz, C. M. P., Jorge L. A. de C. (2022). Delineamento de zonas de manejo para o planejamento de experimentação on-farm na cultura do algodão. *In Congresso brasileiro de agricultura de precisão, 2022,* Campinas, SP.

Wu, C. F. J. (1986). Jackknife, bootstrap e outros métodos de reamostragem em análise de regressão. *Annals of Statistics, 14*(4), 1261-1295.