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OPERATIONAL EFFICIENCY OF THE PNEUMATIC PROBE IN GRAINS SAMPLING AND DECISION-MAKING WITH PYTHON

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ABSTRACT: Soybeans are an essential commodity for the Brazilian agribusiness GDP, as it is a crop exported to various countries. To ensure the quality and health of post-harvest grains, it is essential to follow rigorous storage standards. The export regulations for the commodity are demanding, making it crucial to use technologies to improve operational efficiency in grain selection. In this context, the pneumatic probe and the Python computer language enable process automation and rapid data analysis, contributing to more efficient selection, assertive decision-making, and avoiding contaminations that guarantee grain quality and purity. The present study was conducted in a grain cooperative where two-grain sampling technologies were used, the pneumatic probe and the manual probe. Soybean qualitative data were evaluated in a grain laboratory, and quantitative analyses were performed using the Python language. The pneumatic probe demonstrated greater operational efficiency in relation to quality parameters and soybean grain classification, standing out in greater accuracy in collecting toxic seeds and contaminants. The use of Python language in real-time monitoring proved to be an efficient tool for decision-making.

Keywords: Soybean, Post-harvest, Quality, Storage, Computational language

EFICIÊNCIA OPERACIONAL DA SONDA PNEUMÁTICA NA AMOSTRAGEM DE GRÃOS E TOMADA DE DECISÃO COM PYTHON

RESUMO: A soja é uma commodity essencial para o produto interno bruto do agronegócio brasileiro, sendo uma cultura exportada para diversos países. Para garantir a qualidade e sanidade dos grãos pós-colheita, é imprescindível seguir rigorosos padrões de armazenamento. As regulamentações de exportação da commodity são exigentes, tornando fundamental o uso de tecnologias para aprimorar a eficiência operacional na seleção dos grãos. Nesse contexto, a sonda pneumática e a linguagem computacional Python possibilitam a automação de processos e rápida análise de dados, contribuindo para uma seleção mais eficiente, tomada de decisão assertiva e evitando contaminações que garantem a qualidade e pureza dos grãos. O presente estudo foi realizado em uma cooperativa de grãos onde foram utilizadas duas tecnologias de amostragem de grãos, a sonda pneumática e a sonda manual. Os dados qualitativos soja foram avaliados em um laboratório de grãos e as análises quantitativas foram realizadas por meio da linguagem Python. A sonda pneumática demonstrou ter maior eficiência operacional frente aos parâmetros de qualidade e classificação dos grãos de soja, destacando-se na maior acurácia na coleta de sementes tóxicas e contaminantes. O uso da linguagem Python no monitoramento em tempo real demonstrou ser uma ferramenta eficiente para a tomada de decisão.

Palavras-chaves: Soja, Pós-colheita, Qualidade, Armazenagem, Linguagem computacional

1 INTRODUCTION

Over the years, soybean production in Brazil has presented impressive results for the agricultural sector. It is estimated that for the 2022/2023 harvest, the planting area will have a growth of 4.6% compared to the previous harvest, totaling 43.4 million hectares of productive area and generating an expected record production of 153.5 million tons, a value about 22.2% higher than the 2021/2022 harvest (Soja, 2023). The quality of soybeans in the field is influenced by several factors, such as the genetics of the plant, the agronomic

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practices adopted, and the weather conditions. Among the main quality parameters of soybeans that influence post-harvest and storage, we can highlight the physiological maturity of the grains.

The ideal time for harvesting is when at least 95% of the pods in the field are mature (field maturity, stage R8). Harvesting soybeans outside this range can affect post-harvest, as the producer will have a final product with green grains and higher moisture content (Fher; Caviness, 1977). The moisture range is also an extremely important quality criterion and directly affects the quality of the grains at the time of mechanical harvesting and post-harvest storage. Grains harvested with high moisture have a higher potential for receiving mechanical damage and the proliferation of fungi and bacteria, which rapidly deteriorate the final product, affecting the selling price and its final destination. The ideal range for storage in silos should be between 13 to 15% internal moisture (Barbosa *et al*., 2020).

Other factors that affect the quality of the grains in post-harvest are the presence of broken grains and impurities in the soybean load, such as soil, rocks, plant material, live insects (especially those that cause damage to the stored product "tobacco beetle" - *Lasioderma serricorne*), and seeds considered toxic or contaminants for export ("Federation" - *Senna obtusifolia*, *Cassia obtusifolia*, and *Cassia tora*) and "Corda-de-viola" - *Ipomoea ramosíssima*) (Moraes *et al*., 2022). These factors have an economic impact on the quality of the final product and on the costs of silos and warehouses, with the processes of sampling, cleaning, drying, and storage of the grains, directly affecting the profits of rural producers (Vinhote *et al*., 2021).

Due to the large amount of product that is delivered to silos and warehouses during a specific period of time, which is the harvest season, there is a so-called "crop peak", where it is common to have long lines of trucks waiting to sample the grains and subsequently unload the product. In this sense, the quality control of freshly harvested grains arriving at silos and warehouses must be performed with the highest operational efficiency and in the shortest possible time, as grains, as living biological structures, have a high metabolic rate, mainly influenced by humidity and other impurity factors (Coradi *et al*., 2020), making storage also a factor to be considered in precision agriculture.

The two most commonly used methods for collecting and sampling grains are: the manual sampler, equipment that does not require electrical energy and operates only with the physical work and effort of the sampler on top of the load in the truck to enter the equipment at specific sampling points, and the pneumatic probe, equipment operated via an electrical panel and hydraulic energy, with a rotating range of up to three hundred and sixty degrees and the ability to automatically suck grains that accumulate in layers in the trailer after harvesting in the field (Manis & Sharpe, 2022).

The rapid response regarding the quality data of the soybeans that will be delivered to the warehouse is essential to minimize risks related to storage and to make the correct decision regarding the destination of the load, whether it should be directed only to the silo or go through cleaning and drying processes (Sorour; Uchino, 2004).

Sampling directly impacts the discount values charged by warehouses to rural producers regarding the quality of the delivered product, and the use of technologies capable of operating automatically, combined with computational analysis techniques such as the Python language, which is easily adaptable to databases and designed to analyze, model, and deliver scenarios of the real quality of the product in real-time (Oliveira *et al*., 2022), are important tools to make grain post-harvest safer, maintaining greater sanity, longevity, and quality of the commodity until the moment of its exportation. In this sense, the objective of this work was to analyze the operational efficiency of a pneumatic probe for soybean grain sampling in relation to the manual probe, using real-time computational analysis for better decision-making.

2 MATERIAL AND METHODS

This study was conducted in the premises of a grain receiving warehouse located in the State of São Paulo - Brazil, with a storage capacity of 32 thousand tons of soybeans and total shipping of over 50 thousand tons, during the receiving and dispatch of the soybean crop (Glycine max) for the 2020/2021 harvest. During this period, the 60 kg bag of soybeans was valued at R$148.28 in the State of São Paulo, according to the Center for Advanced Studies in Applied Economics (Cepea, 2021).

For soybean grain sampling, two equipment were used: a pneumatic probe from SAUR brand, model CAS 180/5950[a], with a 180° range of motion, a collection height of up to 5 meters, a horizontal collection range of 295 to 595 cm, and a telescopic arm opening of 300 cm. It has a 3 hp motor for bulk grain suction by air flow (equipment and installation costs for this model in 2023 range from R$180.000,0 to R$200.000,0 according to the manufacturer's budget). A manual probe from Gehaka brand, model DAG-2100/3 with a length of 210 cm, 14 drawers for bulk grain storage, and an approximate weight of 6 kg (equipment acquisition cost in 2023 is R$800,0 according to the manufacturer's website).

Soybean grain samples were taken from a total of twenty loads (n = 20 repetitions) for both treatments, randomly selected based on the arrival of these loads for unloading in the bulk grain unloading sector. Upon arrival at the sampling area, the truck was weighed and grain sampling was performed using both the pneumatic and manual probes on the same load. The sampling method for both treatments followed the parameters of ABNT NBR11161:1990 (ABNT, 2016) and CONAB (2015), which establishes sampling criteria for bulk products (Figure 1).

Figure 1. Pneumatic and manual grain samplers.

Photo: Rodrigo Garcia Brunini (2020)

For each repetition, twelve collection points were randomly selected on the loads. The samples were placed in properly labeled raffia bags for transportation to the grain classification laboratory (Figure 2).

Figure 2. Manual collection procedure, raffia bags containing samples from the pneumatic probe, and from the manual probe.

Photo: Rodrigo Garcia Brunini (2020)

During the sampling procedure, the sampling time in minutes was recorded for both probes for each collected point, as well as the weight in kilograms of the samples (Figure 3).

Figure 3. Weighing of manual probe samples and pneumatic probe samples.

Photo: Rodrigo Garcia Brunini (2020)

The raffia bags were weighed and sent to the analysis and classification laboratory, located within the warehouse unit itself. Upon arrival, the security seal was removed, and the entire sample was placed in a homogenization equipment (quadrant brand Grupo Eagri, stainless steel Multi-Channel model) to separate the standard sample of five hundred grams. Then, the grain classification procedures were initiated (Figure 4) in accordance with Decree No. 6,268 of November 22, 2007, normative instruction (IN) 15/2004, IN 11/2007, and IN 37/2007 from the Ministry of Agriculture, Livestock, and Supply (MAPA), and according to the methodology proposed by MAPA (2008), SENAR (2017), and APROSOJA-MT (2018).

Figure 3. Removal of the sample seal and homogenization of the sample in the grain splitter .

Photo: Rodrigo Garcia Brunini (2020)

Once the sample was homogenized, the quality parameters were classified: weighing of the standard sample of five hundred grams, evaluation of grain moisture, and separation of impurities, broken grains, damaged grains, and green grains. For this purpose, a moisture sensor (Gehaka AGRI brand, model G929, with moisture indication accuracy of +/- 0.1%), a precision digital balance (Ohaus brand, model PR4202BR/E, with a maximum capacity of 4,200 g and accuracy of 0.01 g), and a set of professional sieves for grain classification (Eagri brand, grain model) were used (Figure 5).

Figure 4. Grain moisture sensor, precision digital balance, and set of sieves for grain classification.

Photo: Rodrigo Garcia Brunini (2020)

During the sample classification procedure, seeds from other crops that are considered toxic and contaminants for soybean grain export and human and animal consumption were separated (such as "Fedegoso" (*Senna macranthera*), "Crotalaria" (*Crotalaria sp*.), "corda-de-viola" (*Ipomoea purpurea*), "Carrapichão" (*Xanthium cavanillesii*), "Mamona" (*Ricinus communis*), "girasol" (*Helianthus annuus*), *Sorghum* *halepense*, “Picão-Preto” (*Bidens pilosa*), and treated seeds), as well as the presence of live insects (storage insects) found in the samples. The values of moisture, impurities, broken grains, damaged grains, and green grains present in the 500g standard sample were determined and expressed as a percentage (%).

The tables 1 and 2 highlights some of the discount values applied to the grain load after sampling, analysis, and classification. These discounts are established by the grain warehouse itself during the harvest, and the percentage of discounts is calculated based on the costs of unloading, cleaning, drying, and storing the grains.

Table 1. Discounts of Moisture, Damaged and Impurities (%) on soybeans according to quality parameters at the time of grain delivery*.

Moisture	**Discount**	**Damaged**	**Discount**	**Impurities**	**Discount**
			(%)		
≤ 14,0	0,0	≤ 8,0	0,0	≤ 1,0	0,0
14,1	0,8	8,1	0,1	1,1	0,1
14,2	0,8	8,2	0,2	1,2	0,2
14,3	0,8	8,3	0,3	1,3	0,3
14,4	0,8	8,4	0,4	1,4	0,4
14,5	0,8	8,5	0,5	1,5	0,5
14,6	1,5	8,6	0,6	1,6	0,6
14,7	1,5	8,7	0,7	1,7	0,7
14,8	1,5	8,8	0,8	1,8	0,8
14,9	1,5	8,9	0,9	1,9	0,9
15,0	1,5	9,0	1,0	2,0	1,0
> 15,0	> 1,5	> 9,0	> 1,0	> 2,0	> 1,0

*The table has been adapted to demonstrate some of the discounts applied according to each observed parameter.

Table 2. Discounts of Immature beans and Broken beans (%) on soybeans according to quality parameters at the time of grain delivery*.

Immature beans	**Discount**	**Broken beans**	**Discount**
	(%)		
≤ 8,0	0,0	≤ 30,0	0,0
8,1	0,1	30,1	0,1
8,2	0,2	30,2	0,2
8,3	0,3	30,3	0,3
8,4	0,4	30,4	0,4
8,5	0,5	30,5	0,5
8,6	0,6	30,6	0,6
8,7	0,7	30,7	0,7
8,8	0,8	30,8	0,8
8,9	0,9	30,9	0,9
9,0	1,0	31,0	1,0
> 9,0	> 1,0	> 31,0	> 1,0

*The table has been adapted to demonstrate some of the discounts applied according to each observed parameter.

Python is a programming language widely used in various areas for the development of software solutions. It is a tool to be tested as a popular option for Brazilian agribusiness companies that seek solutions for analysis and advanced data analysis techniques that would be difficult or impossible to identify manually, directly impacting decision-making (Cruz; Mayer; Arantes, 2022).

The data was stored and compiled in a database with dedicated real-time programming for outputting the sanitary quality information of the cargo, the correct destination of the grains at the time of unloading, whether directly to the silo or requiring cleaning and drying steps before storage. In addition, the calculation of discounts to be applied according to the quality and health parameters of the grains mentioned above. To make decision-making more efficient and faster, the Python language (Van Rossum, 2009) was used as the base structure in data analysis and scenario construction, together with several statistical packages (Pandas Development Team, 2021).

In Figure 6, it is possible to verify a part of the method applied with Python (Python Software Foundation, 2021), to verify the possible scenarios for better real-time direction of the loads that arrived at the warehouse according to the emergent need.

Figure 6. Excerpt of the method that generates the best scenario for decision making for the storage of soybeans.

```
# Defining the conditions
if any(tabela['Moisture'][i] > 14 for i in range(len(tabela['Load ID']))):
    if any(tabela['Impurities'][i] > 1 for i in range(len(tabela['Load ID']))):
        if any(tabela['Immature beans'][i] > 8 for i in range(len(tabela['Load ID']))):
            print('send to cleaning and send to dry')
        else:
            print('send to cleaning')
    elif any(tabela['Immature beans'][i] > 8 for i in range(len(tabela['Load ID']))):
        print('send to dry')
    else:
        print('send to dry')
elif any(tabela['Impurities'][i] > 1 for i in range(len(tabela['Load ID']))):
    if any(tabela['Immature beans'][i] > 8 for i in range(len(tabela['Load ID']))):
        print('send to cleaning and send to dry')
    else:
        print('send to cleaning')
elif any(tabela['Immature beans'][i] > 8 for i in range(len(tabela['Load ID']))):
    print('send to dry')
elif any(tabela['Storage insects'][i] == 'Present' for i in range(len(tabela['Load ID']))):
    print('Check the load and notify the producer')
elif any(tabela['Toxic seeds and contaminants'][i] > 0 for i in range(len(tabela['Load ID']))):
    print('Check the load and notify the producer')
else:
    print('send to storage')
```

To build the risk scenario analysis code, the percentage limits of soy quality parameters (moisture, impurities, broken grains, green grains, damaged grains, storage insects, and toxic and contaminant seeds) were taken into consideration, according to tables 1 and 2 provided by the grain receiving company and according to the parameterization proposed by MAPA (2008). The intended response of the model was the appropriate direction of the load within the grain warehouse according to the classification conditions of the standard sample for each load. The possible outputs of the Python model are: Send for cleaning (if the cargo needs cleaning before storage), Send for drying (if the cargo needs to be dried before storage), Send for cleaning and drying (if the cargo needs both cleaning and drying before storage), Check the load and notify the producer (if the cargo needs inspection in case storage insects or contaminating seeds are found in the standard sample), and Send to storage (if the cargo can be directed to storage without the need for other processes).

The data was compiled into a database, with the percentage (%) values of moisture, impurities, broken grains, damaged grains, and green grains present in the standard sample of 500g being determined. Statistical analysis was performed using the Python programming language Python Software Foundation, 2023), and means were evaluated using the Tukey Test (5% probability).

3 RESULTS AND DISCUSSION

According to the data observed in Table 3, it is possible to verify that there were statistical differences for all the observed parameters.

Table 3. Mean values of classification parameters for soybean grains, using sampling by pneumatic probe and manual probe.

Treatment	Parameters					
	Moisture	Impurities	Broken	Damaged	Immature	Time of sampling
			(%)			(min)
Pneumatic probe	12,69 a	1,45 a	11,38 b	2,99 a	0,55 a	8,40 b
Manual probe	11,68 b	0,94 b	14,73 a	1,32 b	0,13 b	15,16 a
DMS*	1,27	0,47	3,65	1,06	0,29	1,03
CV	1,13	1,04	0,97	1,05	1,79	1,68

*DMS - Minimum significant difference. CV - Coefficient of variation (%); means followed by the same letter do not differ statistically from each other by Tukey's test at 5% probability.

The manual probe obtained a lower average humidity than the pneumatic probe (11.68% and 12.69%, respectively). This value may suggest that the pneumatic probe has a capacity to sample deeper layers of the soybean load in the truck, while the manual probe may not reach these layers and extract grains closer to the surface, which are drier due to exposure to sunlight and aeration with the local atmosphere (Jaques *et al*., 2022).

Statistically significant differences were observed for the parameters of impurities (pneumatic 1.45% and manual 0.94%), damaged grains (pneumatic 2.99% and manual 1.32%), and green grains (pneumatic 0.55% and manual 0.13%). It is evident that the quality of sampling through the pneumatic probe is superior and guarantees greater precision regarding the conditions of the load received by the cooperative and the discounts applied to it.

Regarding broken grains, the manual probe performed better with an average of 14.78%, compared to 11.38% for the pneumatic probe. It can be inferred that, due to the manual probe having drawers and a twisting system that opens and closes them during the sample collection, this procedure may break drier grains and thus increase the number of broken grains in the standard classified sample, corroborating studies conducted by Quirino (2019) and Paixão *et al*. (2019), which also observed an influence on grain collection according to the type of equipment used. It is worth noting that, for samples collected with the manual probe, the average weight of grains was 7.3 kg in the raffia bag, while for the pneumatic probe, this average weight was approximately 22.0 kg, highlighting that the quantity of grains sampled in the load will be reflected in the final standard sample in the laboratory. In this sense, the larger the quantity of grains sampled, the better the representation of the real conditions of the load at the time of soybean delivery.

Concerning the average sampling time (time spent on each sampling point on the truck's load), 8.4 minutes were recorded for the pneumatic probe compared to 15.2 minutes for the manual probe (45% less time) to perform the same function, highlighting the importance of using automatic equipment in this stage where trucks wait longer in the unloading queue and there is also a greater potential for accidents to workers who need to climb on top of the load to perform manual sampling. According to Dias, Possamai and Gonçalves (2010), the working time of a machine in relation to the activity performed measures the operational efficiency of equipment, corroborating the data found for the pneumatic probe, which is capable of speeding up the sampling process within the logistics behind a grain-processing unit.

Using risk models with Python language based on all the evaluated quality parameters, it was observed that for the same sampled loads, 60% of them were directly allocated to the grain cleaning and drying processes when using the pneumatic probe, indicating the importance of using this type of computational language technology in analysis for immediate decision-making, Table 4.

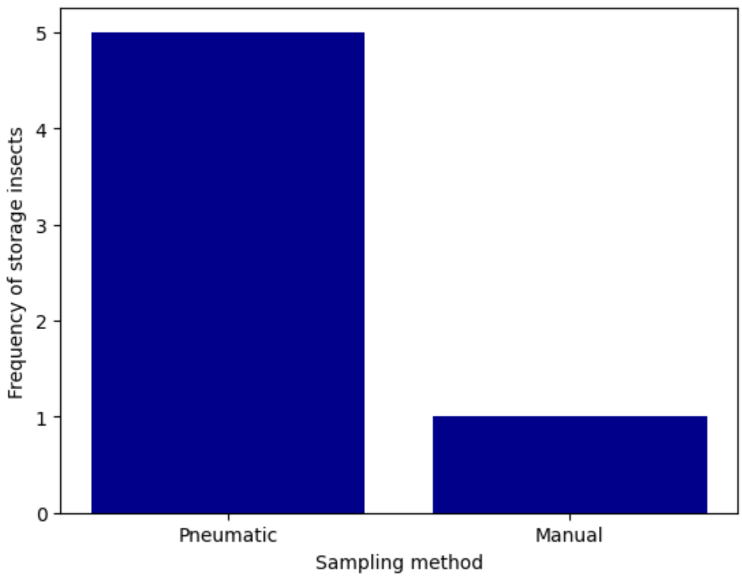
Table 4. Example of the scenarios generated in real time, based on the quality parameters of the soybeans and the computer language method with the Python code.

Load ID	Moisture	Impurities	Broken	Damaged	Immature	Insects	Toxic seeds
1	12.70	2.31	18.02	2.19	1.25	Absent	0
Scenario (Load ID 1): Send to cleaning							
2	14.30	1.10	13.78	1.35	0.02	Absent	0
Scenario (Load ID 2): Send to cleaning and send to dry							
3	12.90	0.50	3.91	1.65	0.00	Absent	0
Scenario (Load ID 3): Send to storage							
4	11.90	1.78	10.02	6.99	0.78	Present	0
Scenario (Load ID 4): Check the load and notify the producer							
5	10.40	0.76	12.34	0.97	0.30	Absent	1
Scenario (Load ID 5): Check the load and notify the producer							

It should be highlighted that if the storage company only uses manual probes and no risk analysis system during the 2020/2021 harvest, it would lose an average of 4.170 bags (R$618.411,00) in drying (0.50%), 6.667 bags (R$988.716,10) in cleaning (0.80%), 417 bags (R$61.841,10) in broken grains (0.05%), 5.250 bags (R$778.575,00) in damaged grains (0.63%), and 1.083 bags (R$160.608,90) in green grains (0.13%), totaling about 17.587 bags in losses (R$2.608.152,10), which could be used to pay for all the investment costs of purchasing and implementing the pneumatic probe technology.

According to Figure 7, it is possible to verify that the pneumatic probe was able to collect more live storage insects (30%) compared to the manual probe (10%) in all 20 classified samples.

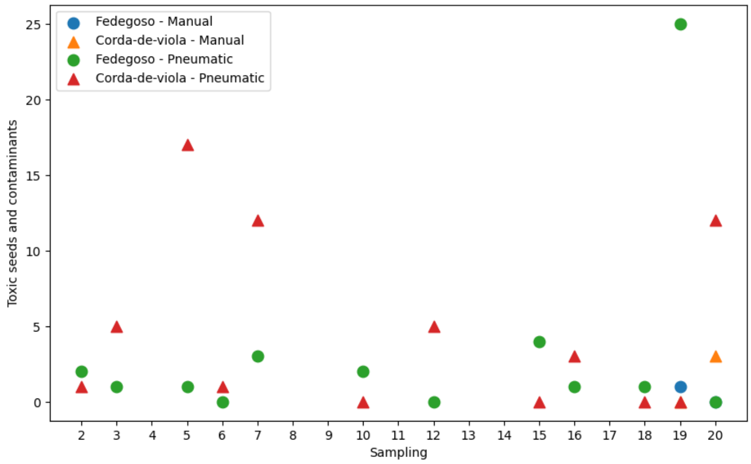
Figure 7. Frequency of storage insect’s occurrence by sampling method.



It is known that the presence of storage insects can pose a phytosanitary risk to the entire load of a silo (approximately 4.000 tons). Considering also a risk for the grain loading processes (sale for export) to customers (Marcos; Karswegaard; Vinicius, 2021).

Figure 8 demonstrate the amount of toxic, contaminant seeds of “Fedegoso” (Senna obtusifolia, Cassia obtusifolia, and Cassia tora), and "Corda-de-viola" (*Ipomoea ramosissima*) found in the twenty evaluated loads through the two sampling methods. It should be noted that there were no occurrences of the other toxic seeds evaluated in this research.

Figure 8. Number of toxic seeds and contaminants occurrence by type of probe and sampling method.



As "Fedegoso" is considered a toxic seed for bulk industry, it deserves greater attention in the process and classification. Thus, the effectiveness of the pneumatic probe, which can more easily extract these seeds during sampling. In Figure 8, it is highlighted that in sample 19, 25 seeds of "Fedegoso" were found in the 500g standard sample collected by the pneumatic probe, while only 1 seed was found in the 500g standard sample collected by the manual probe. In this specific case, appropriate sanitary control measures were taken by the silos department, and the vehicle was not unloaded (Gonzales *et al*., 1994). The producer was informed, and the load was destined for another location. Regarding the seeds of "Corda-de-viola", the same trend of effectiveness of the pneumatic probe in collecting these seeds from the sampled load is observed.

Based on the previously observed data, the use of a pneumatic probe together with computational analysis tools such as the Python language is justified to make decision-making more efficient and safer under a risk analysis of losses per sample evaluated within a grain warehouse, thus making storage a factor to be considered within the field of precision agriculture.

4 CONCLUSION

The pneumatic probe demonstrated greater operational efficiency regarding the quality and classification parameters of soybean grains, as well as operating in less time and with less labor compared to the manual probe.

Sampling soybeans with the manual probe results in a greater collection of broken grains.

The use of Python language for risk analysis is crucial in decision-making regarding costs with cleaning and drying of soybean grains.

The pneumatic probe has greater accuracy in collecting toxic and contaminant seeds.

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