SUGARCANE YIELD MAPPING USING AN ON-BOARD VOLUMETRIC OPTICAL SENSOR

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Abstract.

Few alternatives are available to the sugarcane sector for monitoring crop productivity. However, in recent years, research has been dedicated to developing methods ranging from estimation based on engine parameters to using sensors and artificial intelligence. This study aims to evaluate a new volumetric optical sensor for monitoring sugarcane productivity. The monitoring system is presented based on a database generated during the harvest of a 16 ha field. The data provided by the monitor were filtered, and an exploratory, statistical, and agronomic analysis followed to explore the functionalities that the new technology can offer for decision-making. A cluster analysis was performed to generate productivity zones. Primarily considering the high data collection density of the system (1 Hz) associated with high positioning accuracy (± 0.035 m). The technology demonstrates high potential for use in precision agriculture. Future work with this monitor may test its use for recommending fertilizers at varied rates and identifying Planting failures, among various possible applications.

Keywords.
Artificial intelligence; Proximal sensing; Yield estimation, Precision Agriculture, Digital Agriculture, biomass yield monitor

Introduction

Yield maps play a crucial role in precision agriculture (Molin, J. P. 2002), to achieve more efficiency and sustainability through technological advancements (Smith et al. 2016; Schleifer, 2017). The sugarcane sector, crucial for global food security and sustainable energy transition (Cherubin et al. 2021), faces challenges due to the lack of effective yield mapping solutions (Molin et al. 2024). In the late 1990s initial solutions for sugarcane yield mapping relied on chopper pressure and elevator power sensors (Cox et al. 1999). Different technologies have been emerging, and more recently, a commercial alternative has been developed, deriving production data from hydraulic pressure variations in the chopper system (Maldaner et al. 2021), but sugarcane yield mapping remains limited in adoption (Carrer et al. 2022).

Recently, a new yield monitoring technology for sugarcane, employing 3D cameras (optical

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sensors), has emerged. It offers real-time monitoring by directly estimating production based on material volume on the elevator conveyor and integrating with GPS coordinates. This study aims to evaluate the performance and explore the management potential of this technology using harvest data from a commercial field.

Material and Methods

Sugarcane was planted in May 2021 in a commercial field of 16 ha in southern Brazil, with a row spacing of 1.5 m, and first harvested in May 2022. Data for this study was acquired during the harvest of May 2023, using a John Deere CH570 combine (John Deere, GO, Brazil) containing the systems *Cane Advisor*^{TM},*Harvest Monitor*^{TM} and *Smart Clean*^{TM} (John Deere, SP, Brazil), The ones responsible for monitoring productivity in real-time during the harvesting operation.

The yield monitor operates on a volumetric principle, directly estimating the amount of harvested sugarcane in real-time. 3D digital cameras mounted on the harvester's conveyor track parameters to estimate harvested cane mass, Trash, and cane loss (shredding). Harvesting parameters were adjusted automatically based on these system recommendations. Data was acquired at a frequency of 1 Hz, georeferenced by an integrated GNSS using a StarFire 6000 receiver antenna (John Deere, SP, Brazil) with RTK signal and ±0.035 m accuracy. Data storage included distance and collection time between points, collection date and time, cutting width, operating speed, fuel consumption, estimated Trash mass, estimated sugarcane mass, elevation, longitude, and latitude. System calibration is based on the cumulative mass of three overflows, entered manually or via telemetry, according to the manufacturer’s instructions.

The exploratory data analysis used yield, trash percentage fuel consumption, and harvester speed, based on literature that explored the sugarcane production variability (Maldaner et al. 2021). The data were filtered using an automatic data filtering based on median statistics and sliding window, then was imported to a GIS (QGIS, https://qgis.org/site/) and interpolated by ordinary kriging after variogram adjustment, with the Smart-Map plugin in QGIS GIS software, with a pixel resolution of 3.00 x 3.00 m.

Results and Discussion

In total, at the recommended operating speed for harvesting and with high-resolution data collection frequency from the monitor, 95,206 points were collected in the study area. After filtering, there were 55,724 points remaining for use in the analyses. Table 1 shows the descriptive analysis of some of the data indicated by the productivity monitoring system. Through this, it can be observed that there are areas of productivity with values close to zero, with productivity ranging from 8 to 90 Mg ha-1 from the minimum value to the first quartile. Another notable datum is the elevation, which varies by 16m across the area, relatively steep, which can affect the spatial distribution of productivity (Novais et al., 2007).

Table 1. Statistical summary of the yield and machine data of the study area, obtained by the on-board volumetric monitor.

	Yield	Trash
	Mg ha^{-1}	*kg ha^{-1}*
Mean	116.49	29.53
SD	36.70	14.28
Assim	0.42	0.14
Kurt	0.22	-0.75
Min	8.54	0.00
25%	90.20	18.35
50%	114.53	29.08
75%	139.74	40.30
Max	249.81	73.68

SD: standard deviation; min: minimum value; 25%: 1st quartile; 50%: 2nd quartile; 75%: 3rd quartile; max: maximum value; Assim: assimetry; Kurt: kurtosis.

The productivity map of the area showed pronounced spatial variability of the crop (Figure 2.A), and the interpolation smoothed out the extreme values while maintaining fidelity to the quartiles of the original dataset, an effect known in the literature (Nawar et al., 2017).

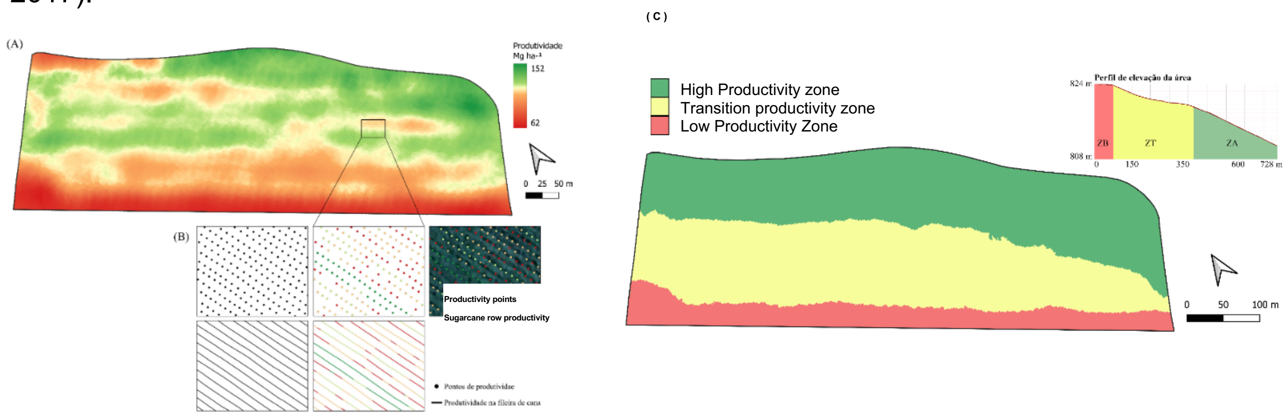

Fig 1. (A) Yield map obtained by ordinary kriging of the filtered points. (B) In detail, a zoom view of the data acquired in the field by the yield monitor, before the interpolation process, in the form of point and line vectors. From the data obtained every 1.00 s by the monitor system, it becomes possible to identify the crop row variability in high spatial resolution. (C) Productivity zones separated by cluster analysis on productivity and area elevation data. In the top left corner, the elevation profile of the area, with colors corresponding to the productivity zones identified by the monitoring data.

However, with the data collected from the productivity monitor in this study, farm management can become even more site-specific. For this purpose, high-density data should be available (Taylor et al., 2019), and preferably, without the use of interpolation, estimating soil and plant parameters directly in the field. This sugarcane harvest, conducted row by row, with a collection frequency of 1.00 Hz and accurate GNSS positioning, allows the manager to identify variability in a meticulous manner, and thus, future studies can investigate strategies for fertilization, recognition of faults in the sugarcane row, line reconstruction, among other approaches.

Conclusion

Based on the data and analyses presented, it can be inferred that the optical productivity sensor for sugarcane, despite requiring attention to the filtering and interpolation steps, can provide data with high frequency, spatial resolution, and precise positioning. Consequently, productivity maps generated with this optical technology have the potential to delineate management zones, increasing the accuracy of the management within the field.

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