Harmonic modeling of coffee biennial bearing to quantify between-plot variability: a Precision Agriculture approach for small-scale agriculture

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A paper from the Proceedings of the
17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture
13-15 July 2026
Porto Alegre, Brazil

Abstract.

Precision Agriculture (PA) practices rely on detecting spatiotemporal variability within a plot to delineate management zones (MZs). This paradigm has been assumed for large-scale plots, yet their adoption in smallholder systems, such as coffee crops under family-based agriculture, remains limited. In this context, within-plot variability is often less operationally relevant than between-plots divergency. Therefore, we assume each plot as a MZ and focus on manage them individually. Moreover, between-plot comparison in small-scale farming must rely on readily available data, such as total yield by plot and season, since traditional PA and digital technologies for data gathering are usually unavailable. Under these premises, we propose a methodology that uses the natural yield alternation of coffee crops (i.e., biennial bearing) as a proxy to characterize between-plot variability in smallholder systems. Approaches to quantify biennial bearing rely on scalar indices (e.g., Hoblyn's Biennial Bearing Index – BBI) that summarize temporal patterns to single values but do not convey the periodic structure of this trait. Thus, we propose a harmonic regression method that numerically expresses biennial bearing based on its oscillatory nature while providing comprehensive plot level comparisons including statistical significance of yield alternation. The methodology comprises three steps. First, we fit simplified harmonic regression models (first harmonic, fixed two-year period), defined as $Yit = \beta_0 + \beta_1\cos(\pi t)$, where Yit is the yield of the i-th plot in the t-th crop season in a time series of four events (t = 1,2,3,4). Second, we calculate the Harmonic Biennial Index ($HBI = |\beta_1|/\beta_0$) to represent the proportion of average yield oscillating between seasons. HBI is a dimensionless measure that isolates true periodic alternation from random variation. HBI values approaching zero indicate negligible biennial oscillation, whereas higher values indicate stronger alternation relative to mean yield. Third, we calculate the Biennial Yield Stability Index (BYSI), as the inverse of the sum of the CV of yield in high and low-yield seasons to quantify within-phase consistency. Plotting HBI and BYSI in a two-

dimensional framework provides information about both yield oscillation intensity and predictability. We applied the method to yield data of ten coffee plots (0.99 to 4.54 ha) with different cultivars and planting year within a single farm. Harmonic models significantly explained ≥81% of yield variation in seven plots, confirming biennial bearing as the dominant temporal pattern. HBI values ranged 18-fold (0.04 to 0.73), validating substantial inter-plot heterogeneity. It was observed cultivar and age-related patterns in biennial bearing models. The joint HBI × BYSI framework grouped plots into distinct patterns, e.g., high-intensity predictable yield alternation or stable non-biennial alternation The harmonic modeling of longitudinal yield data can properly represent biennial bearing as a periodic trait of coffee crops, allowing its quantification and eventual use to detect between-plot variability. Also, the proposed method works without expensive infrastructure for data gathering, extending PA principles to smallholder farming contexts.

Keywords.

Regression analysis, longitudinal data, yield alternation, plot-level management.

Introduction

The identification of spatiotemporal variability within plots is the baseline to perform Precision Agriculture (PA) practices, once it allows the deliniation of pixels or management zones (MZs) presenting homogeneous agronomic features that can support site-specific management, which means applying the inputs according to the inherent requirements of each zone. However, despite this identification being viable in large-scale farming systems through current monitoring technologies, it remains limited in smallholder agriculture. In this case, within-plot subdivision is often impractical but plot-level management may represent a more feasible alternative (Silva et al., 2025). Therefore, the characterization of variability between plots becomes particularly relevant to perform PA practices in such scenarios.

In this sense, some crops such as coffee cultivation offer a unique opportunity to check this possible contrast based on historical yield data, which are often available even in farms with low technological infrastructure. One of the most distinctive biological characteristics of coffee plants is biennial bearing, i.e., a natural alternation between high and low yield growing seasons. Thus, assuming that each plot within a farm presents natural and management related differences that influence yield, one can use this crop response as a proxy to quantify the underlying between plots divergencies.

Although biennial bearing has been described using scalar indices, such as the Hoblyn's Biennial Bearing Index – BBI reported by Hoblyn et al. (1936), these approaches translate yield alternation into a single numerical value but do not explicitly represent its natural periodic structure. In this context, the use of mathematical functions to describe complex biological phenomena has a long tradition in quantitative biology. Classical examples include logistic growth models for populations (Pearl & Reed, 1920; Pearl, 1927; Tsoularis & Wallace, 2002), growth curves for plants and animals (Richards, 1959; Teleken et al., 2017), and harmonic models used to characterize circadian and seasonal biological rhythms (Halberg, 1960; Cornelissen, 2014). Rather than reproducing every source of variation, these models aim to capture the principal structure of a biological process in a parsimonious and interpretable way. Similarly, regardless biennial bearing of crops is influenced by numerous factors, a mathematical representation could provide a valuable description of their dominant underlying patterns.

Following this perspective, we hypothesize that biennial bearing can be described as a biological phenomenon with periodic component that can be represented through harmonic functions. Nevertheless, we assume that this model fitting do not intended to predict coffee yield itself, as proposed by Carvalho et al. (2005), but rather to provide a functional description of the biennial variation in each plot within a farm. Consequently, it could allows comparisons between them based on the intensity, synchronization (i.e., phase), and stability of their yield oscillations.

Therefore, this study aims to assess whether a harmonic modeling can represent coffee biennial bearing as a seasonal biological process and become a potential framework to characterize between-plot variability within smallholder systems, following PA concepts.

Material and methods

Dataset description

We test our hypothesis using a dataset comprising yield data (represented in 60 kg bags ha^{-1} unit) over four consecutive crop seasons (2017/2018 to 2020/2021) of ten coffee plots belonging to a single farm. All evaluated plots were cultivated with Arabica coffee (*Coffea arabica* L.) cultivars. However, the plots differed in cultivar, age, area, and management history, including pruning events. Table 1 presents additional information about the plots, including yield.

Table 1. Summary of the coffee plots' features and yield in four consecutive growing seasons.

Plot	Cultivar	Spacing (m)		Area (ha)	Planting year	Yield (60 kg bags ha^{-1})			
		Rows	Plants			2017/2018	2018/2019	2019/2020	2020/2021
P01	Acaiá IAC 474 - 19	2.80	1.80	4.54	1998	45.89	7.43	42.41	6.54
P02	Bourbon Amarelo IAC J19	3.70	0.60	0.99	2015	26.42	41.99	56.16	47.65
P03	Catuaí Amarelo IAC 100	1.75	1.00	1.23	1970	30.59	42.47	26.99	41.94
P04	Catuaí Amarelo IAC 100	3.70	0.75	1.54	2013	30.54	50.75	40.60	44.08
P05	Catuaí Amarelo IAC 100	1.75	1.00	2.40	1980	24.75	90.55	32.89	84.47
P06	Catuaí Amarelo IAC 100	2.70	1.00	3.09	1981	17.39	21.14	15.83	20.30
P07	Mundo Novo IAC 379 - 19	3.70	0.60	3.61	2015	15.45	46.21	41.88	52.52
P08	Mundo Novo IAC 388 - 17 - 1	1.75	1.00	2.07	1995	39.84	114.31	35.60	75.48
P09	Mundo Novo IAC 388 - 17 - 1	3.00	2.00	2.28	1965	62.56	24.45	67.84	16.62
P10	Mundo Novo IAC 388 - 17 - 1	3.00	2.00	3.40	1980	53.09	34.14	53.73	37.68

Biennial bearing modeling

Biennial bearing was modeled for each plot using a simplified harmonic regression with a fixed period of two years, according to Equation 1:

$$Y_{it}=\beta_0+\beta_1\cos(\pi t)+\varepsilon_{it} \quad ; \quad t=1, 2, 3, 4 \qquad (3)$$

Where: Y_{it} is the yield of the i-th plot in the t-th season, β_0 represents mean yield, and β_1 represents the biennial oscillation component.

The models were fitted through ordinary least squares (OLS) method and their performance was evaluated using the coefficient of determination (R^2). To summarize biennial bearing intensity, the Harmonic Biennial Index (HBI) was calculated as described by Equation 2.

$$HBI_i=|\beta_{1i}|/\beta_{0i} \qquad (2)$$

Where: $|\beta_{1i}|$: non-negative value of the amplitude regarding the yield oscillation of the i-th plot throughout the evaluated period; β_{0i}: average yield of the i-th plot over the evaluated period. To a straightforward interpretation, higher HBI values indicate stronger yield alternation relative to mean productivity.

To complement the HBI, a Biennial Yield Stability Index (BYSI) was calculated from the coefficient of variation (CV) of yields observed within high and low yield phases to quantify how similar yield levels are in years belonging to the same biennial phase, as proposed by Equation 3.

$$BYSI_i=1/(CV_{i\ high}+CV_{i\ low}) \qquad (3)$$

High BYSI values indicate greater consistency of yield responses across biennial cycles. Finally, HBI and BYSI were analyzed together to classify plots according to both biennial intensity and stability.

Results and discussion

Biennial bearing modeling performance

Figure 1 presents the yield variation in each coffee plot and the corresponding harmonic model fitting. The models adequately represented coffee biennial bearing in most plots. Seven of the ten evaluated plots presented R^2 values ≥ 0.81, indicating that biennial oscillation explained most of the observed temporal variability in yield.

The fitted models also highlight the differences in the concurrency of yield oscillations of the plots in a single farm. In our case, most plots exhibited the same phase, with yield peaks occurring during the same crop seasons, whereas a smaller group showed an opposite phase, indicating contrasting production dynamics within the same farm.

The proposed HBI ranged from 0.04 (P02) to 0.73 (P01), representing an approximately 18-fold difference in biennial bearing intensity between the plots. Plots exhibiting higher HBI values also tended to present lower yields during off-years, reinforcing the biological interpretation of the index. These results demonstrated the usefulness of the proposed index to characterize the heterogeneity in the magnitude of yield alternation. Therefore, it indicated that plots may respond differently to local growing conditions and management practices.

HBI also allowed us to observe that cultivar and crop age appeared to influence biennial bearing intensity. Thus, the only Acaiá plot showed the strongest biennial behavior, whereas Catuaí plots generally exhibited lower oscillation magnitudes. Intermediate age coffee plants tended to present greater biennial intensity than younger plants, indicating that crop development stage may influence the expression of yield alternation, which is expected and then quantified through the proposed methodology.

The BYSI complemented HBI by revealing differences in the stability of yield responses. In this sense, some plots exhibited strong biennial oscillations associated with consistent production patterns, whereas others showed irregular behavior despite presenting similar biennial intensity. Thus, we could observe plots with high-intensity predictable yield alternation (e.g., P01: HBI = 0.73, BYSI = 0.07) and stable non-biennial yield alternation (e.g., P06: HBI = 0.10, BYSI = 0.04).

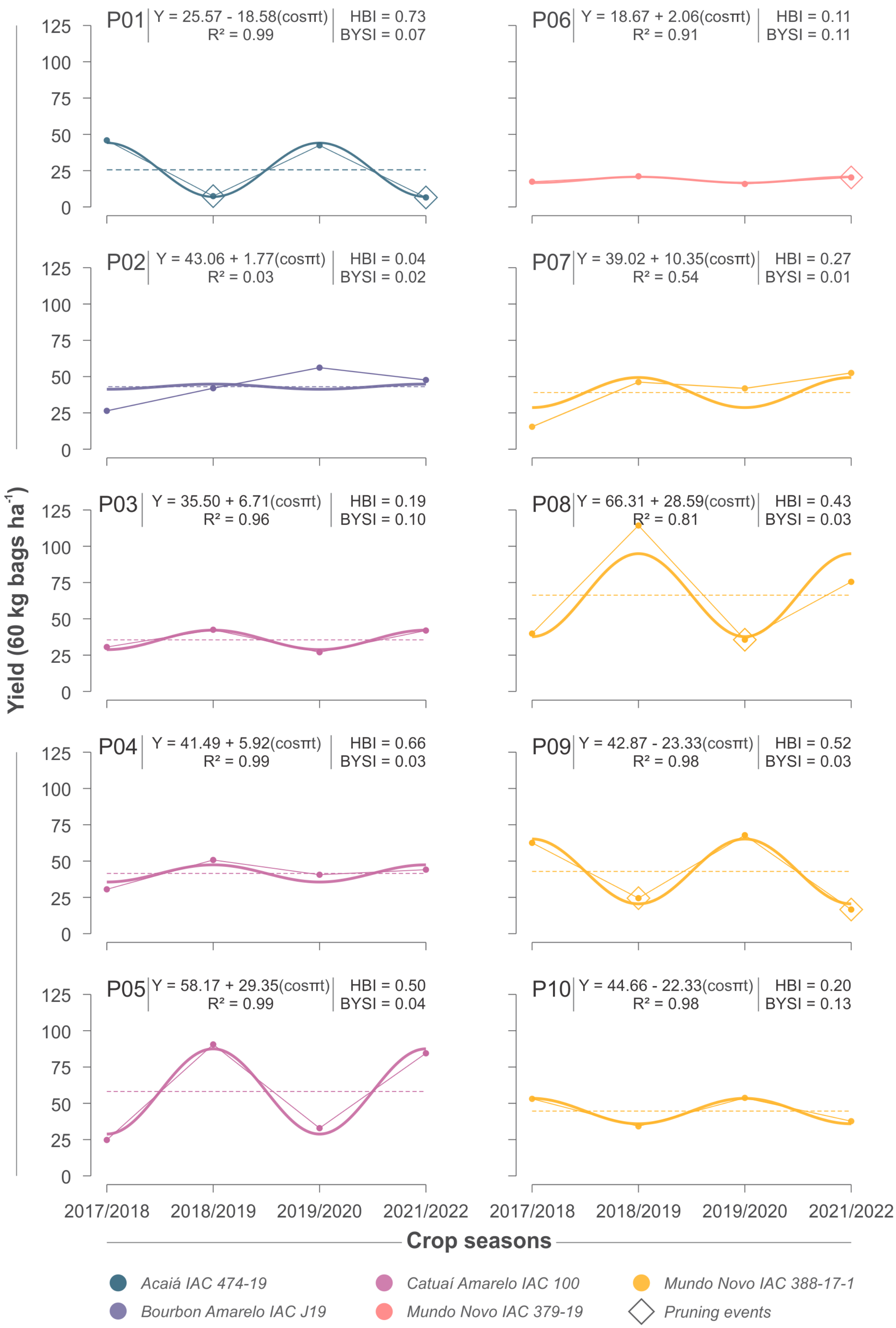

Fig 1. Harmonic models' fitting to coffee yield data of four consecutive growing seasons in ten different plots (P01 to P10) of a single farm.

Conclusion

Harmonic regression can represent coffee biennial bearing as a periodic phenomenon and provide a robust framework for detecting between-plots variability within a single farm. Once the proposed approach requires only historical yield records, it offers a simple and accessible framework for extending PA principles to small-scale coffee production systems.

Acknowledgments

This study was financed, in part, by the São Paulo Research Foundation (FAPESP), Brazil. Process Number 2022/09319-9 and 2025/01962-8. The authors thank the Brazilian Micro and Small Business Support Service – SEBRAE, Minas Gerais, for data availability.

References

Carvalho L. G. d., Sediyama G. C., Cecon P. R., & Alves H. M. R. (2005). Aplicação da análise harmônica por séries de Fourier para a previsão de produtividade da cultura do café no estado de minas gerais. *Engenharia Agrícola*, 25(3), 732–741, doi: https://doi.org/10.1590/S0100-69162005000300019.

Cornelissen G. (2014). Cosinor-based rhythmometry. *Theoretical Biology and Medical Modelling*, 11(1), 16. https://doi.org/10.1186/1742-4682-11-16.

Hoblyn T. N., Grubb N. H., Painter A. C., & Wates B. L. (1936) Studies in biennial bearing – I. *Journal of Pomology and Horticultural Science*, 14(1), 39–76, doi: https://doi.org/10.1080/03683621.1937.11513464.

Hofman M. A. (2001). Seasonal rhythms of neuronal activity in the human biological clock: A mathematical model. *Biological Rhythm Research*, 32(1), 17–34, doi: https://doi.org/10.1076/brhm.32.1.17.7281.

Pearl R. (1927). The growth of populations. *The Quarterly Review of Biology*, 2(4), 532–548, doi: https://doi.org/10.1086/394288.

Pearl R., & Reed L. J. (1920). On the rate of growth of the population of the United States since 1790 and its mathematical representation. *Proceedings of the National Academy of Sciences*, 6(6), 275–288, doi: https://doi.org/10.1073/pnas.6.6.275.

Richards F. J. (1959). A flexible growth function for empirical use. *Journal of Experimental Botany*, 10(2), 290–301, doi: https://doi.org/10.1093/jxb/10.2.290.

Silva E. R. O. d., Silva T. L. d.; Wei M. C. F., Souza R. A. d., & Molin J. P. (2025). Spatial and Temporal Variability Management for All Farmers: A Cell-Size Approach to Enhance Coffee Yields and Optimize Inputs. *Plants*, 14(2), 169, doi: https://doi.org/10.3390/plants14020169.

Teleken J. T., Galvão A. C., & Robazza W. da S. (2017). Comparing non-linear mathematical models to describe growth of different animals. *Acta Scientiarum. Animal Sciences*, 39(1), 73–81, doi: https://doi.org/10.4025/actascianimsci.v39i1.31366.

Tsoularis A., & Wallace, J. (2002). Analysis of logistic growth models. *Mathematical Biosciences*, 179(1), 21–55, doi: https://doi.org/10.1016/S0025-5564(02)00096-2.