
# Site-specific nutrient management in citrus: agronomic, economic and energy implications of variable rate fertilization

G. V. Bedum[1]; M. S. Gelain[1]; R. C. Filho[1]; E. R. O. Silva[2]; J. P. Molin[1]; A. F. Colaço[1]

[1]Laboratory of Precision Agriculture, "Luiz de Queiroz" College of Agriculture – University of São Paulo, SP, Brazil

[2]Center for Carbon Research in Tropical Agriculture, "Luiz de Queiroz" College of Agriculture – University of São Paulo, SP, Brazil

**A paper from the Proceedings of the**

**17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture**

**13-16 July 2026**

**Porto Alegre, Brazil**

***Abstract.***

*Brazilian citrus production faces growing challenges due to rising production costs, the intensification of climatic and biotic stresses, and the increasing demand to optimize input use, particularly fertilizers. In this context, precision agriculture can provide the conceptual and operational basis for site-specific management by allowing fertilizer applications to be adjusted according to the spatiotemporal variability of the production system. This study evaluated, under commercial-scale conditions, the effects of variable-rate fertilization (VR) compared with fixed-rate fertilization (FR) over six consecutive growing seasons (2012–2017), integrating agronomic, energy, and economic analyses. The experiment was conducted in the state of São Paulo, Brazil, in ten commercial orchards of approximately 25 hectares each, five managed under VR fertilization and five under FR fertilization. Nitrogen, phosphorus, potassium, and lime were applied under both management systems. In the VR-managed areas, fertilizer recommendations were established based on georeferenced soil or leaf sampling and yield maps from the previous season. Under FR management, nutrient recommendations were defined based on composite soil samples and applied uniformly within each orchard block. Yield was quantified during harvest by georeferencing big bags. The results indicated that VR fertilization increased yield by an average of 6.29% compared with FR fertilization. Although the study encompassed multiple growing seasons, no temporal consistency was observed in the yield response to the treatments. Regarding total input use, only potassium differed between the systems, with higher application rates under VR management. Partial nutrient balances showed distinct responses between the management systems. For N, VR resulted in balances closer to zero. For $P_2O_5$, differences varied among growing seasons, with larger surpluses under VR in the initial years and lower surpluses in subsequent seasons. For $K_2O$, VR resulted in higher balances, associated with the larger application rates under this management system. The energy analysis showed that embodied energy per unit of production was primarily influenced by annual yield and fertilization intensity, with no statistical differences between the management systems. Nevertheless, a trend toward lower energy consumption per kilogram of oranges was observed in the VR-managed areas.*

The authors are solely responsible for the content of this paper, which is not a refereed publication. Citation of this work should state that it is from the Proceedings of the 17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture. EXAMPLE: Last Name, A. B. & Coauthor, C. D. (2026). Title of paper. In Proceedings of the 17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture and Brazilian Congress on Precision and Digital Agriculture.

*From an economic perspective, VR involved additional costs associated with data collection and processing and with the greater number of field operations required for input-specific applications. However, over the entire study period, VR resulted in a slightly higher partial economic return, with an average increase of US$ 191.21 per hectare. Overall, VR and FR showed similar performance, and the gains provided by VR applications were modest when observed. This result was partly related to the criteria adopted to develop the variable-rate prescriptions, as they were based on traditional fertilizer recommendation tables used in citrus production in São Paulo. Thus, despite the use of spatially variable information on soil and crop conditions, the rules guiding the recommendations remained generalized. This limitation reinforces the importance of developing more specific recommendation models adapted to local soil, plant, and climatic conditions and capable of integrating spatial soil fertility information and crop responses.*

***Keywords.***
*Commercial-scale experiment, long-term field evaluation, spatial variability*

# 1. Introduction

Citrus production stands out as one of the most economically and socially important agricultural sectors worldwide, with citrus crops cultivated in more than 100 countries (Liu et al. 2012). Brazil holds a prominent position in this sector, with an annual production of approximately 18.5 million Mg, of which approximately 15.7 million Mg correspond to oranges, consolidating the country as the world's largest producer of this fruit. The state of São Paulo accounts for more than 75% of national production and constitutes the main Brazilian hub for citrus production, processing, and exports (FAO 2025; IBGE 2025). Despite its relevance, citrus production faces challenges related to the incidence of pests and diseases, declining orchard productivity, climate variability, and economic pressure arising from market price volatility (Bozma et al. 2023; Li et al. 2020; Rasera et al. 2023). In this context, strategies capable of increasing input-use efficiency are essential to enhance the resilience and profitability of production systems (Limayem et al. 2024; Qin et al. 2016).

Precision agriculture (PA) is widely used to understand and manage spatial variability in agricultural systems (Cherubin et al. 2022; Molin et al. 2015). In citrus orchards, tools such as yield mapping, remote sensing, georeferenced soil sampling, and geostatistical analyses make it possible to identify spatial patterns related to plant vigor, nutrient status, and soil fertility (Colaço et al. 2020b; Tantalaki et al. 2019; Zeng et al. 2025). Among the strategies enabled by these tools, variable-rate fertilizer application stands out because it allows nutrient rates to be adjusted according to spatial variability within the orchard, aiming to improve fertilizer-use efficiency, reduce waste, and minimize environmental impacts (Colaço et al. 2020a; Costa et al. 2022; Termin et al. 2023).

However, these technologies are still evaluated predominantly based on agronomic and operational indicators, such as yield, fertilizer consumption, and the spatial variability of soil properties. Approaches that simultaneously integrate agronomic, economic, and energy indicators remain uncommon (Bahmutsky et al. 2024). This gap is relevant because reductions in input consumption or increases in yield do not necessarily translate into greater profitability, as the benefits may be insufficient to offset the additional implementation costs (Griffin et al. 2018; Lowenberg-DeBoer and Erickson 2019). Reviews conducted by Colaço and Bramley (2018) and Lambert and Lowenberg-DeBoer (2000) indicate that approximately 25% of studies report negative or inconclusive economic outcomes.

Additionally, variable-rate fertilizer recommendations face a structural limitation. Although PA technologies provide spatially explicit information on soil and plant conditions, available agronomic recommendations are frequently derived from experiments conducted under average soil and climate conditions. Consequently, regional recommendation guidelines may not adequately represent the specific response of each production environment (Bramley et al. 2019;

Colaço and Molin 2017; Colaço et al. 2020a). This mismatch is particularly relevant for fruit crops because nutrient demand and responses to fertilization vary according to phenological stage, crop load, vegetative growth, and stress conditions, in addition to being influenced by the cumulative effects of management practices over successive production cycles (Agustí et al. 2022; Xu et al. 2024).

In citrus orchards, these responses should be evaluated over a timeframe compatible with the perennial nature of the crop. Changes in soil fertility, plant nutrient status, and vegetative growth may require several production cycles to become fully evident (Mira-García et al. 2024; Grieve et al. 2007; Wang et al. 2026; Xu et al. 2024). Moreover, reserves accumulated in woody tissues may temporarily mitigate nutrient deficiencies and delay the expression of treatment effects (Zhao et al. 2025; Xiong et al. 2025). Nevertheless, long-term experiments evaluating site-specific fertilization strategies in citrus orchards remain scarce (Colaço and Molin 2017; Srivastava and Das 2017).

Within this context, the present study was based on the following research question: Can variable-rate fertilizer application improve system-efficiency indicators, such as yield, economic performance, nutrient balance, and energy efficiency, compared with conventional fixed-rate management? To address this question, the performance of variable-rate fertilization was evaluated in a commercial-scale experiment conducted over six production cycles, considering agronomic, economic, and energy aspects.

## 2. Materials and methods

### 2.1. Study areas

The study was conducted from 2012 to 2017 in commercial orange-producing areas located in the municipality of Iaras, São Paulo State, Brazil (Figure 1). According to the Köppen–Geiger climate classification, the region has a Cwa climate, characterized as humid subtropical with dry winters and rainy summers (Alvares et al. 2013). Mean annual precipitation is approximately 1,400 mm, concentrated primarily between October and March. The orchards were rainfed, with no supplemental irrigation. The predominant soils were classified as medium-textured Oxisols, according to USDA Soil Taxonomy (Soil Survey Staff 2022).

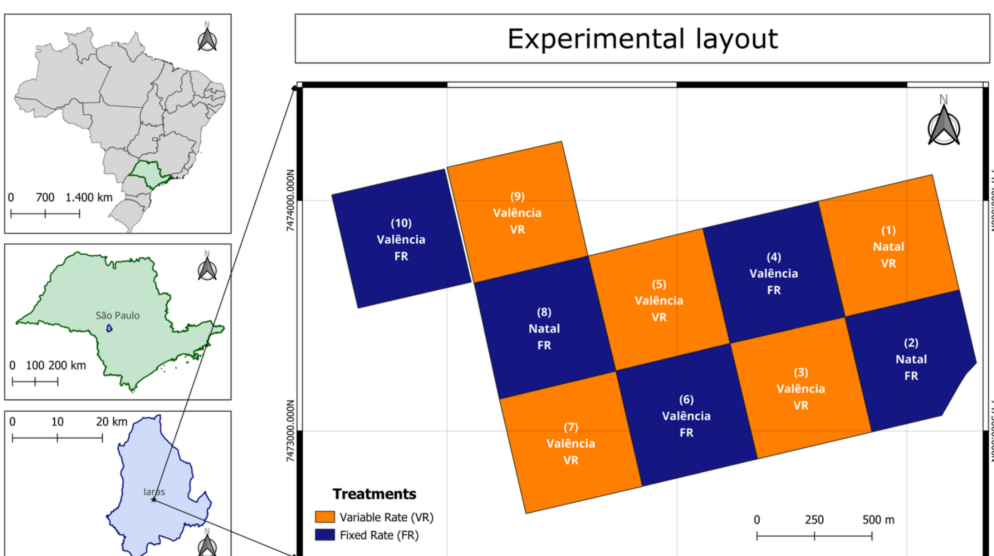


**Fig. 1 Location and experimental layout of the citrus orchards evaluated in Iaras, São Paulo State, Brazil.**

The experimental area totaled approximately 250 ha and comprised ten commercial orchard blocks of approximately 25 ha each, all established using the same planting spacing. Regarding scion cultivars, seven orchard blocks were planted with 'Valencia' and three with 'Natal'. Two soil fertility management strategies were evaluated, variable-rate (VR) and fixed-rate (FR) applications of nitrogen, phosphorus, potassium, and lime. The experimental design was established at the field scale, with each orchard block representing an experimental unit. Five replicates were used per treatment.

## 2.2. Data collection and processing

Variable-rate recommendations were defined by integrating soil fertility maps, leaf N concentrations, and yield maps. Soil samples were collected annually using a sampling grid with a density of one sample $ha^{-1}$. For nitrogen, leaf samples were collected on a grid using the same sampling density adopted for soil sampling. Soil fertility data were subjected to geostatistical analysis and interpolated at a spatial resolution of 10 m. When spatial dependence was identified, interpolation was performed by kriging using Vesper 1.6 software. When spatial dependence was not detected, the inverse distance weighting method was applied using QGIS software.

Yield maps were generated by georeferencing harvest big bags. Initially, the raw data were subjected to a cleaning procedure to remove duplicate points with overlapping coordinates. Subsequently, a representative area was delineated for each harvest unit (big bag), according to the methodology described by Colaço et al. (2020b). Yield was estimated by assuming a uniform mass for the big bags and dividing this value by the area of the respective Voronoi polygon. To remove inconsistent values resulting from the limited positional accuracy of the GNSS receiver, the data were filtered using MapFilter 2.0 software (Maldaner et al. 2022). After filtering, the yield data were also subjected to geostatistical analysis and interpolated by ordinary kriging at a spatial resolution of 10 m.

Fertilizer rates for nitrogen, phosphorus, and potassium were based on the regional recommendations proposed by van Raij et al. (1997), which are widely used in the state of São Paulo. The rates were defined according to expected yield and nutrient concentrations in leaves (N) or soil (P and K). To avoid discontinuities among recommendation classes, the values were interpolated using multiple linear regression, according to the methodology described by Colaço and Molin (2017). Expected yield was estimated from the yield map of the previous growing season and adjusted by an annual increase or reduction factor defined by the farm technical team based on orchard age and expected canopy growth. Lime requirements were determined using the base saturation method, with a target base saturation of 70%, as recommended for citrus by van Raij et al. (1997). Under VR management, each input was applied separately, resulting in nine operations per growing season: three N applications, three $K_2O$ applications, two $P_2O_5$ applications, and one lime application.

Under FR management, fertilizer recommendations followed the conventional management practices adopted by the farm. Soil sampling was performed using one composite sample per orchard block, consisting of 25 randomly collected subsamples. Fertilizer rates were defined according to the recommendations of van Raij et al. (1997), considering the mean soil nutrient concentrations and the average expected yield of each orchard block. Lime recommendations followed the same criterion adopted under VR management. Under this system, four mechanical operations were performed per growing season: three fertilizer applications and one lime application.

Rainfall data were provided directly by the farm. Complementary climate data, including temperature and soil moisture, were acquired through the NASA POWER platform. Elevation data were obtained from the ALOS PALSAR platform through remote sensing and processed using QGIS software.

## 2.3. Energy and nutrient balance

The energy assessment was based on embodied energy (MJ $kg^{-1}$), calculated as the ratio between total energy input and fruit yield. The energy associated with fertilization was estimated by multiplying the applied rates of N, $P_2O_5$, $K_2O$, and lime by their respective energy coefficients, as described in Table 1. Energy consumption associated with fuel use was determined according to the methodology proposed by Romanelli and Milan (2010), based on the product of hourly fuel consumption, effective field capacity, and the energy index. Machinery depreciation was calculated according to equipment useful life and mass. Energy consumption associated with the collection and processing of soil and yield data was estimated according to Colaço et al. (2020a), considering the labor time required, which corresponded to 5.0 h $ha^{-1}$ under VR management and 0.3 h $ha^{-1}$ under FR management.

**Table 1. Energy coefficients of the inputs applied in the production system.**

| Input | Unit | Energy index (MJ $unit^{-1}$) | Reference |
|---|---|---|---|
| Nitrogen (N) | kg | 74 | Pellizzi (1992) |
| Phosphorus ($P_2O_5$) | kg | 12.5 | Pellizzi (1992) |
| Potassium ($K_2O$) | kg | 6.7 | Devasenapathy et al. (2009) |
| Lime | kg | 1.6 | Ferraro Jr (1999) |
| Labor | h | 2.2 | Ferraro Jr (1999) |
| Fuel (Diesel) | L | 45.7 | Boustead and Hancock (1979) |
| Machine depreciation | kg | 32.5 | Mantoam et al. (2016) |

Subsequently, partial nutrient balances were calculated for N, $P_2O_5$, and $K_2O$. For each nutrient, the balance was obtained as the difference between the amount applied through fertilization and the amount removed by fruit harvest. Nutrient removal was estimated based on the yield of each orchard block and the coefficients proposed by IPNI (2020), corresponding to 1.9 kg of N, 0.4 kg of $P_2O_5$, and 1.8 kg of $K_2O$ per megagram of oranges produced. Positive balances indicate that nutrient inputs exceeded removal through harvest, whereas negative balances indicate that removal exceeded the amount applied, suggesting that soil or plant reserves contributed to meeting crop nutrient demand (Gaj and Bellaloui 2012).

## 2.4. Economic analysis

The economic analysis was based on total fertilization cost, gross revenue, and the partial economic return of each treatment. Gross revenue was estimated as the product of fruit yield and the average price of an orange box between October and January (CEPEA 2025). Partial economic return was calculated as the difference between gross revenue and total fertilization cost. Input prices were obtained from the annual averages reported by CONAB (2025). All monetary values were adjusted using the IGP-M price index (IPEA 2025) and expressed as present values for January 2025. Subsequently, values in Brazilian reais were converted into US dollars using an exchange rate of BRL 6.1619 per US$ 1.00. The use of average values was intended to reduce the influence of temporal fluctuations in input and output prices on the economic comparison between treatments.

Total fertilization cost was estimated as the sum of the expenses associated with acquiring information for agronomic recommendations, purchasing inputs, and applying fertilizers and soil amendments (Equations 1–6). Information acquisition costs included the collection and analysis of soil fertility and yield data. Input costs included nitrogen, phosphorus, and potassium fertilizers, as well as lime. Application costs included labor, machinery operation, fuel consumption, maintenance and repairs, and machinery fixed costs. Machinery fixed costs included depreciation, interest, insurance, taxes, and other expenses associated with equipment ownership. The purchase prices adopted were US$ 45,362.79 for the tractor and US$ 11,354.65 for the fertilizer spreader, according to the data reported by CONAB (2025). For the VR treatment, an additional cost of US$ 981.89 was added to the spreader purchase price, corresponding to the kit used to control the application rate. Useful life was set at 12,000 h for the tractor and 2,400 h for the fertilizer spreader. Equipment salvage value was set at 30% of the initial purchase price. Maintenance and repair costs were estimated at 95% of machinery purchase price over its useful life (ASABE 2011), whereas insurance and tax costs were set at 1.0% of equipment value.

[1] $\mathrm{TFC} = \mathrm{CAI} + \mathrm{FC} + \mathrm{AC}$

[2] $\mathrm{AC} = (\mathrm{LC} + \sum_{n} \mathrm{MOC}) \times \alpha$

[3] $\mathrm{MOC_n} = (\mathrm{FCC_n} + \mathrm{MR_n} + \mathrm{FHC_n})$

[4] $\mathrm{FCC_n} = \mathrm{TP} \times \mathrm{S} \times \mathrm{DP}$

[5] $\mathrm{MR_n} = \frac{95\% \times \mathrm{IV}}{\mathrm{t}}$

[6] $\mathrm{FHC} = \frac{\left(\mathrm{IV} \times \left(\left[\frac{(1-\mathrm{RV})}{\mathrm{b}}\right] + \left[\frac{(1+\mathrm{RV})}{2} \times \mathrm{i}\right] + \mathrm{FAI}\right)\right)}{\mathrm{t}}$

Where: TFC represents the total fertilization cost (US$ ha$^{-1}$); CAI, cost of acquiring information on soil fertility and yield (US$ ha$^{-1}$); FC, fertilizer cost (US$ ha$^{-1}$); AC, fertilizer application cost (US$ ha$^{-1}$); LC, labor cost (US$ 2.27 h$^{-1}$, average wage practiced in the region); MOC, hourly machinery operating cost (US$ h$^{-1}$); n, number of implements, such as the tractor and the fertilizer spreader; α, operational field-time coefficient (0.3 h ha$^{-1}$); FCC, fuel consumption cost (US$ h$^{-1}$); MR, maintenance and repair cost (US$ h$^{-1}$) (ASABE 2011); FHC, fixed hourly cost (US$ h$^{-1}$) (Milan and Rosa 2015); TP, tractor power (100 cv); S, fuel consumption rate (0.121 cv$^{-1}$ h$^{-1}$) (ASABE 2011); DP, average diesel price in the year (ANP 2025); IV, initial machinery value (US$); RV, residual value, expressed as a decimal fraction of the initial value (Milan and Rosa 2015); b, useful life of the asset in years; t, useful life of the asset in hours; i, interest rate, fixed at 12.82% per year (IPEA 2025); and FAI, shelter, insurance, and taxes factor, expressed as a decimal.

The statistical analysis was performed to compare the performance of the FR and VR management strategies. Initially, the data were subjected to an F-test to assess the homogeneity of variances between management strategies. When no significant differences between variances were detected, Student's *t*-test for two independent samples assuming equal variances was applied. When variances differed significantly, Welch's *t*-test, which does not assume equal variances, was used. A significance level of 5% was adopted for all tests.

# 3. Results and discussion

## 3.1. Input consumption

Variable-rate applications altered the distribution profile of inputs over the evaluated growing seasons but did not result in an overall reduction in the amounts applied (Figure 2). Considering the entire study period, mean N rates were similar between management systems, with 177.42 kg ha$^{-1}$ under VR and 177.94 kg ha$^{-1}$ under FR. A similar pattern was observed for $P_2O_5$, with mean rates of 60.15 and 59.18 kg ha$^{-1}$, respectively. For $K_2O$, VR resulted in a significantly higher rate of 158.99 kg ha$^{-1}$, compared with 119.92 kg ha$^{-1}$ under FR, corresponding to an increase of 32.58%. For lime, a numerical reduction of 20.61% was observed under VR (1,227.24 kg ha$^{-1}$) compared with FR (1,545.86 kg ha$^{-1}$), although the difference was not statistically significant.

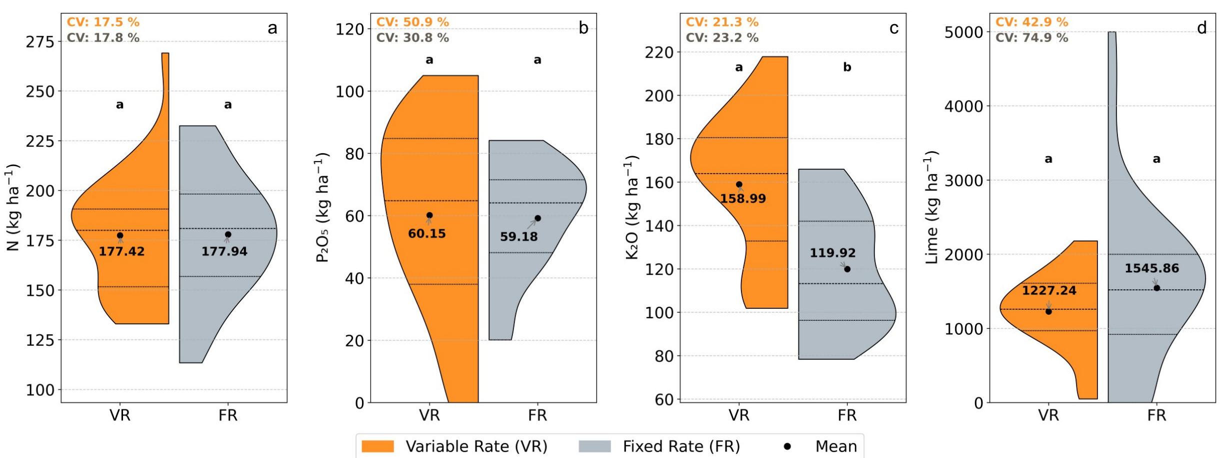


**Fig. 2 Distribution of nitrogen (a), phosphorus (b), potassium (c), and lime (d) application rates under variable-rate and fixed-rate management. Different letters indicate a significant difference between management strategies (*p* < 0.05).**

The lack of systematic input savings does not necessarily represent a limitation of VR management. Site-specific application adjusts fertilizer rates according to initial soil fertility and the spatial variation in crop demand, which may result in either increases or reductions in the amounts of inputs applied in specific areas of an orchard block (Bahmutsky et al. 2024; Termin et al. 2023). In citrus orchards, Colaço and Molin (2017) also observed contrasting responses: VR reduced N and $P_2O_5$ use in both orchards, whereas changes in $K_2O$ and lime use varied among orchard blocks. These results reinforce that the performance of VR management depends on local conditions and on the strategy used to translate spatially explicit information into fertilizer recommendations (Colaço et al. 2020a; Nawar et al. 2017).

Potassium is one of the nutrients most extensively removed by citrus crops, which continuously depletes soil reserves and requires adequate replenishment over successive production cycles (Alva et al. 2006). Although both treatments showed fluctuations in soil potassium concentrations over the evaluated period, FR management, which received lower mean $K_2O$ rates, had a larger proportion of the area with potassium concentrations classified as low (Figure 3), according to van Raij et al. (1997). By incorporating soil potassium concentrations and nutrient removal estimated from yield maps into the fertilizer recommendation calculations, VR management resulted in greater nutrient replenishment and a smaller proportion of areas with low soil potassium concentrations.

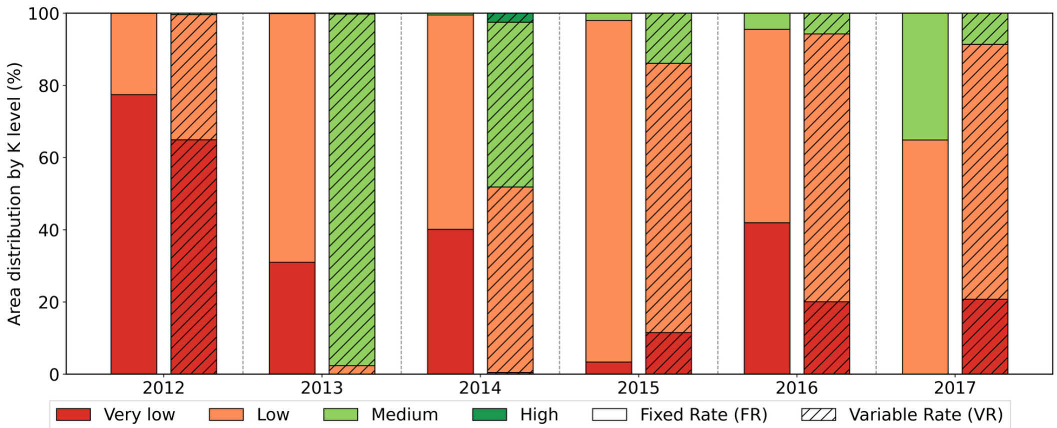


**Fig. 3 Percentage of the area classified according to soil K levels under FR and VR management from 2012 to 2017. Interpretation classes: very low, < 0.8; low, 0.8–1.5; medium, 1.5–3.0; and high, > 3.0 $mmol_c\ dm^{-3}$ (van Raij et al. 1997).**

## 3.2. Yield

Annual yield analyses in perennial crops should be interpreted with caution because interannual variation may occur (Agustí et al. 2022; Goldschmidt and Sadka 2021). Although VR fertilization is commonly associated with consistent increases in production, its greatest potential lies in improving input-use efficiency (Späti et al. 2021; Colaço and Molin 2017). Over the six-year evaluation period, yield gradually increased under both management strategies (Figure 4a), reflecting the vegetative and productive development of the orchard during its early establishment phase. VR resulted in higher mean yields in 2012 (25.64 Mg $ha^{-1}$), 2013 (29.77 Mg $ha^{-1}$), 2015 (43.33 Mg $ha^{-1}$), and 2017 (91.14 Mg $ha^{-1}$), whereas FR resulted in higher yields in 2014 (44.71 Mg $ha^{-1}$) and 2016 (51.10 Mg $ha^{-1}$). Among these differences, only the contrast observed in 2017 was statistically significant. The yield increase observed in that year was associated with orchard physiological maturity and higher precipitation during the period, conditions that may have favored the expression of differences between the management strategies.

Considering the mean yield over the six-year evaluation period, VR resulted in a 6.29% increase in yield compared with FR, although the difference was not statistically significant (Figure 4b). This result reinforces that the assessment of VR fertilization in citrus orchards should be conducted from a long-term perspective and encompass multiple dimensions of analysis, including yield, economic performance, environmental impacts, and resource-use efficiency, because its benefits may vary among production cycles (Bahmutsky et al. 2024; Colaço et al. 2020a). More consistent responses may be constrained by the adoption of generalized recommendation algorithms developed for average soil and crop conditions and, therefore, less sensitive to local responsiveness to applied nutrients (Colaço et al. 2020a; Nawar et al. 2017).

Thus, the performance of VR management depends not only on the quality of the spatial data collected but also on the ability of the decision model to translate these data into agronomically appropriate prescriptions for the conditions of each production environment (Bramley et al. 2019; Guerrero and Mouazen 2021).

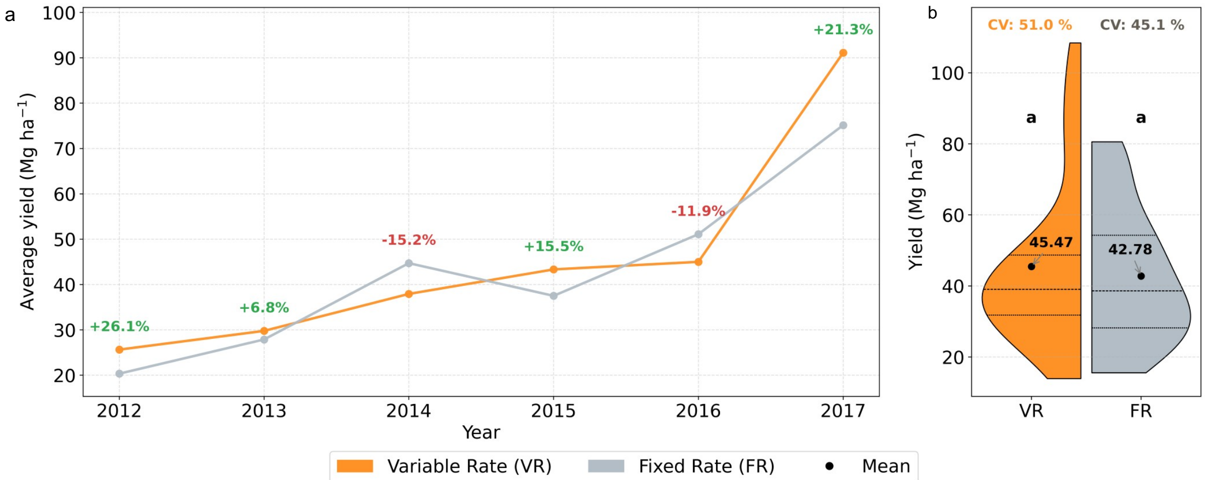


**Fig. 4 Average yield: (a) temporal variation from 2012 to 2017 and (b) average yield considering the entire evaluation period. Different letters indicate a significant difference between management strategies ($p$ < 0.05).**

## 3.3. Energy and financial analysis

Embodied energy per kilogram of oranges produced ranged from 0.22 to 0.72 MJ kg$^{-1}$ over the evaluated period (Figure 5), with no statistically significant differences between treatments. In 2013 and 2014, embodied energy under VR management was higher than under FR management, with increases of 5.61% and 9.49%, respectively, due to the higher nutrient inputs and greater lime use in those growing seasons. In the remaining years (2012, 2015, 2016, and 2017), VR resulted in lower values, with reductions ranging from 4.18% to 11.06%. Overall, embodied energy was more sensitive to interannual variation in yield and nutrient demand than to the application method. Nevertheless, the trend toward lower values under VR management reinforces its potential to improve input-use efficiency (Angnes et al. 2021). The energy required for mechanized operations represented a relatively small fraction of total energy input, corresponding to 8.50% and 4.55% under VR and FR management, respectively. However, this energy requirement was 82.37% higher under VR management, reflecting the greater number of field operations required by this system.

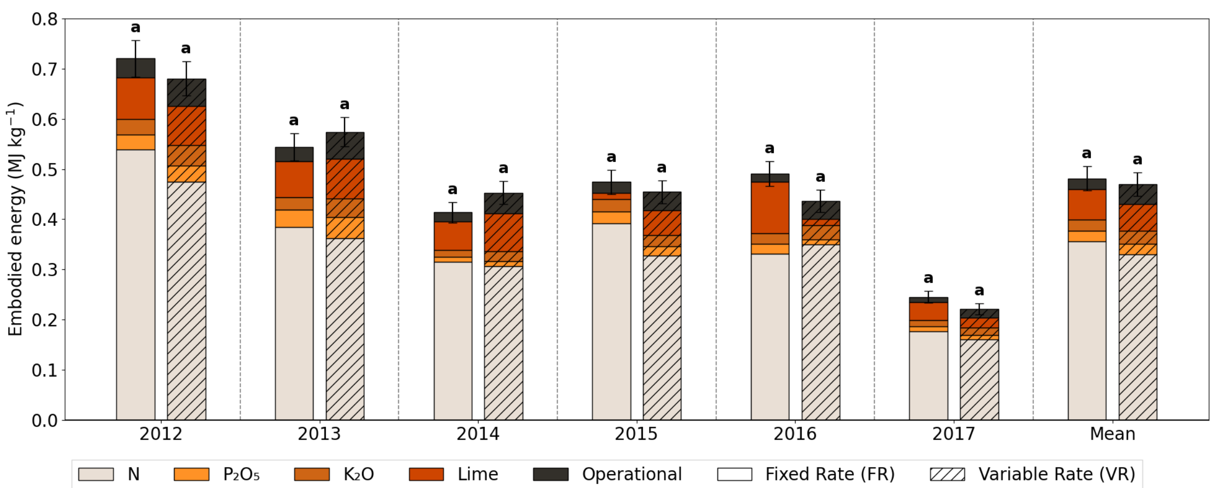


**Fig. 5 Historical variation in embodied energy (MJ kg$^{-1}$) from 2012 to 2017. Different letters indicate a significant difference between management strategies ($p$ < 0.05).**

N was the input with the greatest contribution to the energy balance, accounting for 74.08% and 70.26% of the total energy associated with fertilization under FR and VR management, respectively. This result is consistent with those reported by Colaço et al. (2020a) and Ozkan et al. (2004). The higher energy demand during the initial years reflects the lower yield of the orchard during its establishment phase, an expected pattern in perennial crops. This analysis considered only inputs directly associated with fertilization. Therefore, studies evaluating the entire production cycle have reported a greater contribution of fuel and crop protection products to the total energy balance (Franco Junior et al. 2014), although fertilizers remain a major component in all scenarios.

Regarding economic performance, gross revenue followed the productive development of the orchards, with the highest values observed in 2016 and 2017 (Figure 6a). VR resulted in numerically higher gross revenue than FR in 2012, 2013, 2015, and 2017, with differences of US$ 203.01, US$ 153.38, US$ 554.10, and US$ 2,026.21 ha$^{-1}$, respectively. However, the difference between management strategies was statistically significant only in 2017, indicating that the effect of variable-rate fertilization on gross revenue was not consistent across growing seasons. Although the implementation of site-specific fertilization involves additional steps for data collection, processing, and interpretation, as well as the separate application of each input, these components did not result in a substantial increase in mean cost. Considering the entire evaluation period, the cost of VR management was US$ 4.44 ha$^{-1}$ higher than that of FR management, with no statistically significant difference between the management strategies (Figure 6b).

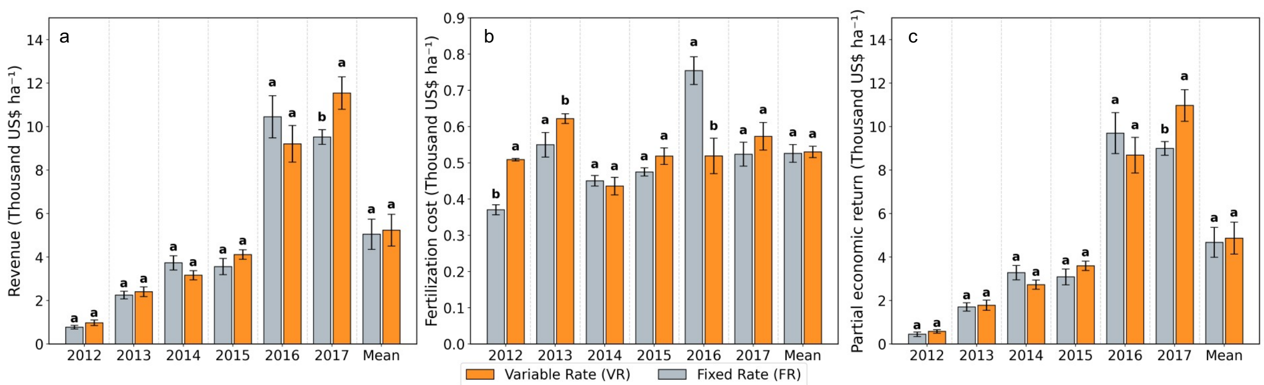


**Fig. 6 Historical series of gross revenue (a), fertilization cost (b), and partial economic return (c) for the variable-rate (VR) and fixed-rate (FR) fertilization systems from 2012 to 2017. Different letters indicate a significant difference between management strategies ($p$ < 0.05).**

Considering the mean values over the six growing seasons, VR resulted in a partial economic return US$ 191.21 ha$^{-1}$ higher than that of FR, although the difference was not statistically significant. This gain varied over the years, primarily following fluctuations in yield. In 2017, despite a US$ 49.54 ha$^{-1}$ higher cost associated with fertilization management, the greater gross revenue obtained under VR offset this additional cost and resulted in a partial economic return US$ 1,976.67 ha$^{-1}$ higher than that of FR (Figure 6c). This pattern suggests that the economic benefit of VR does not necessarily arise from a direct increase in gross revenue, but rather from the balance between additional implementation costs and the gains associated with more appropriate input allocation.

When fertilization costs and revenue normalized by year are analyzed jointly, distinct patterns are observed for the VR and FR strategies (Figure 7). The regressions indicate positive trends for both systems, demonstrating that increased fertilization costs were directly associated with increased normalized revenue. However, this relationship was more pronounced under VR, as indicated by the steeper slope compared with FR. Under the evaluated conditions, this pattern suggests that normalized revenue tended to respond more strongly to increased fertilization costs under VR, indicating greater potential returns associated with investment in inputs (Zeraatpisheh et al. 2020).

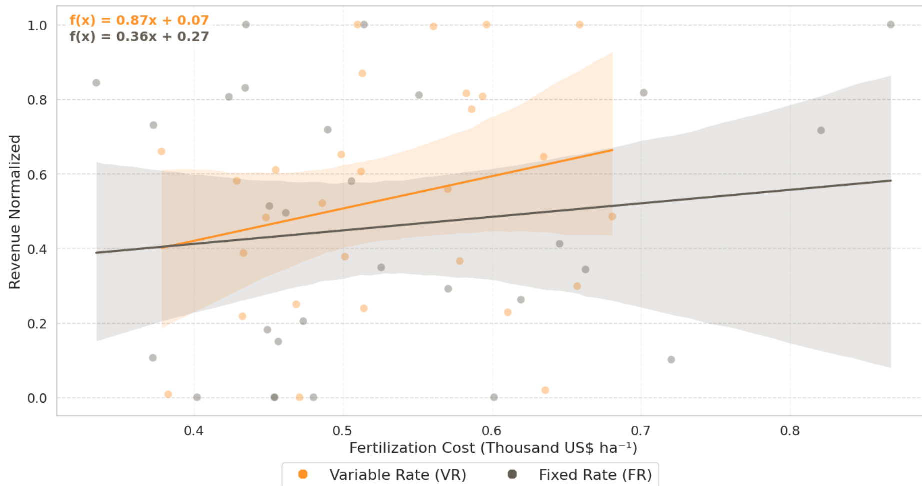


**Fig. 7 Relationship between fertilization cost and normalized revenue for the variable-rate and fixed-rate fertilization systems. The lines represent the trends fitted by linear regression for each system.**

The regression lines intersected at US$ 392.16 ha$^{-1}$. This value can be interpreted as an economic break-even point between the evaluated systems. Below this fertilization cost, FR tends to result in higher estimated normalized revenue, whereas above this threshold, VR tends to show superior relative performance, indicating greater economic feasibility of site-specific fertilization under scenarios in which efficiency gains offset the additional costs associated with the technology.

### 3.4. Partial nutrient balances and future perspectives

Partial nutrient balances were positive under both treatments throughout the evaluated period, indicating that nutrient inputs through fertilization exceeded removal by harvested fruit (Figure 8). For N, no statistically significant difference was observed between management strategies. However, VR resulted in a slightly lower mean balance than FR, with values of 88.97 and 94.88 kg ha$^{-1}$, respectively. In addition, VR showed lower values in five of the six growing seasons, suggesting a closer alignment between N supply and crop removal.

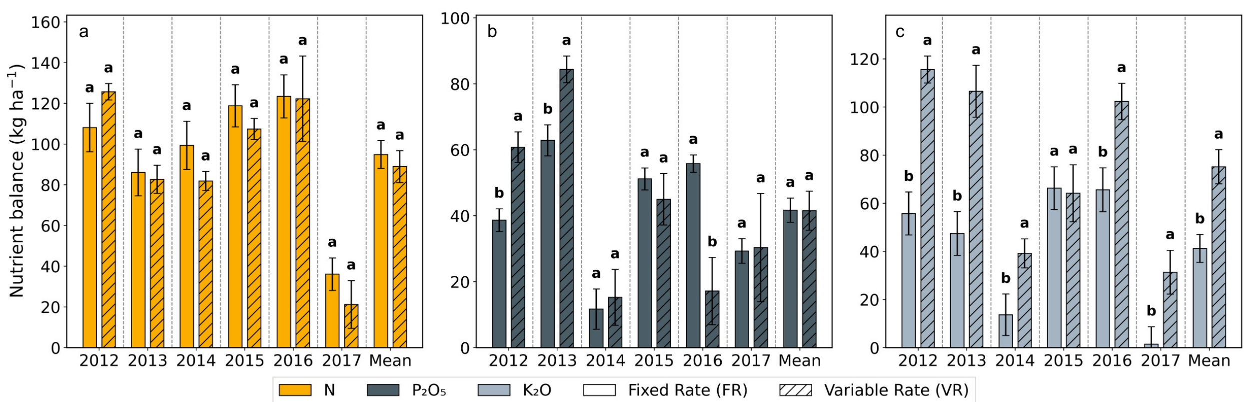


**Fig. 8 Historical variation in the nutrient balance of N (a), $P_2O_5$ (b), and $K_2O$ (c), expressed in kg ha$^{-1}$, from 2012 to 2017. Different letters indicate a significant difference between management strategies (*p* < 0.05).**

For $P_2O_5$, the mean balance over the evaluated period was similar between treatments, with 41.53 kg ha$^{-1}$ under VR and 41.70 kg ha$^{-1}$ under FR. However, the temporal dynamics differed between management strategies. During the initial years, VR resulted in larger surpluses, with values of 60.82 kg ha$^{-1}$ in 2012 and 84.40 kg ha$^{-1}$ in 2013, compared with 38.65 and 62.89 kg ha$^{-1}$ under FR, respectively. This greater initial input was consistent with the subsequent increase in soil P concentrations. Therefore, differences decreased from 2015 onward, and in 2016, the balance under VR was 53.87% lower than that under FR, indicating a progressive adjustment of the recommendation. The most pronounced differences were observed for $K_2O$. The mean partial balance was 75.19 kg ha$^{-1}$ under VR and 41.24 kg ha$^{-1}$ under FR, corresponding to an increase of 82.32%. VR resulted in a larger balance in five of the six growing seasons, with particularly pronounced differences in 2012 and 2013, when balances reached 115.60 and 106.56 kg $ha^{-1}$, compared with 55.79 and 47.45 kg $ha^{-1}$ under FR, respectively. This pattern was associated with the higher $K_2O$ rates applied under variable-rate management.

The integrated analysis of the results did not demonstrate consistent superiority of variable-rate application. The observed fluctuations indicate that its benefits were modest and dependent on the nutrient and production cycle, possibly because the characterization of soil variability, plant nutrient status, and yield, although necessary, does not alone ensure prescriptions tailored to local crop responses. In citrus orchards, Colaço and Molin (2017) and Colaço et al. (2020a) also observed distinct responses among orchards, with greater benefits of VR in the area with greater intrinsic variability. In a broader context, Colaço et al. (2024) demonstrated that simplified agronomic rules may retain substantial errors when applied spatially and, in some cases, perform worse than uniform-rate application.

The temporal variability of the results also indicates that fertilization strategies should not be evaluated in isolation from the broader factors controlling yield. A complementary analysis of the same experimental database conducted by Wei et al. (2026), using machine learning models, explainable artificial intelligence techniques, and causal discovery methods, identified convergence across analytical approaches regarding the relevance of yield stability zones, growing season, and rainfall. The fertilization strategy was relevant in some associative analyses but did not have a direct connection with yield in the causal network. Nevertheless, the results reinforce that yield responses emerge from interactions among soil, climatic, temporal, and orchard-related factors and are not determined exclusively by the spatial distribution of fertilizer rates.

Therefore, conducting on-farm experiments with contrasting fertilizer rates under commercial conditions may contribute to a deeper understanding of crop responses to fertilization. When repeated over different production cycles, these trials make it possible to quantify optimal crop responses and assess how soil, yield, and climate attributes influence these responses (Bullock et al. 2019; Lacoste et al. 2022). The gradual consolidation of this information may support the refinement of decision rules and, subsequently, the evaluation of spatially explicit prescriptions more closely aligned with the specific conditions of each orchard (Colaço et al. 2024). Thus, advances in site-specific fertilization depend not only on the spatial distribution of fertilizer rates but also on improving the agronomic knowledge underlying their prescription.

# 4. Conclusions

The results demonstrated that VR fertilization modified input distribution and partial nutrient balances but did not show consistent superiority over FR fertilization based on yield, economic, and energy criteria. Over the six evaluated production cycles, VR resulted in a mean yield increase of 6.29% and an increase of US$ 191.21 $ha^{-1}$ in partial economic return, in addition to showing a trend toward lower embodied energy per unit of production in most growing seasons. However, these differences were not statistically significant. N and $P_2O_5$ rates were similar between management strategies, whereas VR resulted in higher $K_2O$ application rates, contributing to greater nutrient replenishment and a smaller proportion of areas with low soil K concentrations.

Partial nutrient balances showed distinct responses depending on the nutrient and production cycle. For N, VR resulted in closer alignment between inputs through fertilization and removal by harvested fruit. For $P_2O_5$, the larger surpluses observed during the initial years gradually decreased over successive growing seasons. For $K_2O$, the higher rates applied under VR management resulted in larger balances. Taken together, these results indicate that the benefits of site-specific fertilization were modest and variable over time, reinforcing that the spatial allocation of fertilizer rates alone does not ensure greater efficiency when prescriptions remain based on generalized regional criteria.

## 5. References

Agustí, M., Reig, C., Martínez-Fuentes, A., & Mesejo, C. (2022). Advances in Citrus Flowering: A Review. *Frontiers in Plant Science*, Volume 13:868831. https://doi.org/10.3389/fpls.2022.868831

Alva, A. K., Dirceu Jr, M., Paramasivam, S., Patil, B., Dou, H., & Sajwan, K. S. (2006). Potassium Management for Optimizing Citrus Production and Quality. *International Journal of Fruit Science*, *6*(1), 3–43. https://doi.org/10.1300/J492v06n01_02

Alvares, C. A., Stape, J. L., Sentelhas, P. C., Gonçalves, J. L. de M., & Sparovek, G. (2013). Köppen's climate classification map for Brazil. *Meteorologische Zeitschrift*, 22(6), 711–728. https://doi.org/10.1127/0941-2948/2013/0507

Angnes, G., Martello, M., Faulin, G. D. C., Molin, J. P., & Romanelli, T. L. (2021). Energy Efficiency of Variable Rate Fertilizer Application in Coffee Production in Brazil. *AgriEngineering*, *3*(4), 815–826. https://doi.org/10.3390/agriengineering3040051

ANP. (2025). Agência Nacional do Petróleo, Gás Natural e Biocombustíveis. (National Agency of Petroleum, Natural Gas and Biofuels). *Série histórica de preços de combustíveis e de GLP*. https://www.gov.br/anp/pt-br/centrais-de-conteudo/dados-abertos/serie-historica-de-precos-de-combustiveis

ASABE - American Society of Agricultural and Biological Engineers. (2011). ASAE D497.7: *Agricultural machinery management data*. http://elibrary.asabe.org/abstract.asp?aid=36431&t=1&redir=&redirType=

Bahmutsky, S., Grassauer, F., Arulnathan, V., & Pelletier, N. (2024). A review of life cycle impacts and costs of precision agriculture for cultivation of field crops. *Sustainable Production and Consumption*, *52*, 347–362. https://doi.org/10.1016/j.spc.2024.11.010

Boustead, I., & Hancock, G. F. (1979). Handbook of industrial energy analysis. Chichester, UK: Ellis Horwood Ltd.

Bozma, G., Urak, F., & Bilgiç, A. (2023). The Asymmetric Vertical Price Volatility Spillover in the Citrus Market. *Erwerbs-Obstbau*, *65*(4), 915–926. https://doi.org/10.1007/s10341-022-00785-5

Bramley, R. G. V, Ouzman, J., & Gobbett, D. L. (2019). Regional scale application of the precision agriculture thought process to promote improved fertilizer management in the Australian sugar industry. *Precision Agriculture*, *20*(2), 362–378. https://doi.org/10.1007/s11119-018-9571-8

Bullock, D. S., Boerngen, M., Tao, H., Maxwell, B., Luck, J. D., Shiratsuchi, L., et al. (2019). The Data-Intensive Farm Management Project: Changing Agronomic Research Through On-Farm Precision Experimentation. *Agronomy Journal*, *111*(6), 2736–2746. https://doi.org/10.2134/agronj2019.03.0165

Cherubin, M. R., Damian, J. M., Tavares, T. R., Trevisan, R. G., Colaço, A. F., Eitelwein, M. T., et al. (2022). Precision Agriculture in Brazil: The Trajectory of 25 Years of Scientific Research. *Agriculture*, *12*(11). https://doi.org/10.3390/agriculture12111882

Colaço, A. F., & Bramley, R. G. V. (2018). Do crop sensors promote improved nitrogen management in grain crops? *Field Crops Research*, *218*, 126–140. https://doi.org/10.1016/j.fcr.2018.01.007

Colaço, A. F., & Molin, J. P. (2017). Variable rate fertilization in citrus: a long term study. *Precision Agriculture*, *18*(2), 169–191. https://doi.org/10.1007/s11119-016-9454-9

Colaço, A. F., Pagliuca, L. G., Romanelli, T. L., & Molin, J. P. (2020a). Economic viability, energy and nutrient balances of site-specific fertilisation for citrus. *Biosystems Engineering*, *200*, 138–156. https://doi.org/10.1016/j.biosystemseng.2020.09.007

Colaço, A. F., Trevisan, R. G., Karp, F. H. S., & Molin, J. P. (2020b). Yield mapping methods for manually harvested crops. *Computers and Electronics in Agriculture*, *177*, 105693.

https://doi.org/10.1016/j.compag.2020.105693

Colaço, A. F., Whelan, B. M., Bramley, R. G. V, Richetti, J., Fajardo, M., McCarthy, A. C., et al. (2024). Digital strategies for nitrogen management in grain production systems: lessons from multi-method assessment using on-farm experimentation. *Precision Agriculture*, *25*(2), 983–1013. https://doi.org/10.1007/s11119-023-10102-z

CONAB. (2025). Companhia Nacional de Abastecimento. (National Supply Company). *Preços*. https://www.gov.br/conab

Costa, L., Kunwar, S., Ampatzidis, Y., & Albrecht, U. (2022). Determining leaf nutrient concentrations in citrus trees using UAV imagery and machine learning. *Precision Agriculture*, *23*(3), 854–875. https://doi.org/10.1007/s11119-021-09864-1

Devasenapathy, P., Senthilkumar, G., & Shanmugam, P. M. (2009). Energy management in crop production. *Indian Journal of Agronomy*, *54*, 80–89. https://doi.org/10.59797/ija.v54i1.4771

FAO. (2025). Food and Agriculture Organization of the United Nations *Production: Crops and livestock products*. https://www.fao.org/faostat/en/#data/QCL

Ferraro Jr, L.A. (1999). An evaluation method of production systems and sustainability. Master's dissertation. Brazil, Luiz de Queiroz College of Agriculture, University of São Paulo. https://doi.org/10.11606/D.11.1999.tde-20220207-214730

Franco Junior, N. C., Milan, M., & Romanelli, T. L. (2014). Energy demand in citrus production under varied operational efficiency values. *Engenharia Agrícola*, *34*. https://doi.org/10.1590/S0100-69162014000400014

Gaj, R., & Bellaloui, N. (2012). Evaluation of phosphorus and nitrogen balances as an indicator for the impact of agriculture on environment: A comparison of a case study from Poland and Mississippi US. *Agricultural Sciences*, *3*(2), 317. http://dx.doi.org/10.4236/as.2012.32036

Goldschmidt, E. E., & Sadka, A. (2021). Yield Alternation: Horticulture, Physiology, Molecular Biology, and Evolution. In Horticultural Reviews (pp. 363–418). https://doi.org/10.1002/9781119750802.ch8

Grieve, A. M., Prior, L. D., & Bevington, K. B. (2007). Long-term effects of saline irrigation water on growth, yield, and fruit quality of 'Valencia' orange trees. *Australian Journal of Agricultural Research*, *58*(4), 342–348. https://doi.org/10.1071/AR06198

Griffin, T. W., Shockley, J. M., & Mark, T. B. (2018). Economics of Precision Farming. In *Precision Agriculture Basics* (pp. 221–230). https://doi.org/10.2134/precisionagbasics.2016.0098

Guerrero, A., & Mouazen, A. M. (2021). Evaluation of variable rate nitrogen fertilization scenarios in cereal crops from economic, environmental and technical perspective. *Soil and Tillage Research*, *213*, 105110. https://doi.org/10.1016/j.still.2021.105110

HORTIFRUTI BRASIL/CEPEA. (2025). Centro de Estudos Avançados em Economia Aplicada. (Center for Advanced Studies on Applied Economics). *Preços médios dos hortifrutícolas*. https://www.hfbrasil.org.br/br/banco-de-dados-precos-medios-dos-hortifruticolas.aspx

IBGE. (2025). Instituto Brasileiro de Geografia e Estatística. (Brazilian Institute of Geography and Statistics). *Produção agropecuária: Laranja.* https://www.ibge.gov.br/explica/producao-agropecuaria/laranja/br

IPEA. (2025). Instituto de Pesquisa Econômica Aplicada. (Institute for Applied Economic Research). *Ipeadata*. http://www.ipeadata.gov.br/Default.aspx

IPNI. (2020). International Plant Nutrition Institute. https://www.npct.com.br/npctweb/npct.nsf/article/calculadora.

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., et al. (2022). On-Farm Experimentation to transform global agriculture. *Nature Food*, *3*(1), 11–18.

https://doi.org/10.1038/s43016-021-00424-4

Lambert, D., & Lowenberg-DeBoer, J. (2000). Precision agriculture profitability review. West Lafayette: Site-Specific Management Center, Purdue University.

Li, S., Wu, F., Duan, Y., Singerman, A., & Guan, Z. (2020). Citrus Greening: Management Strategies and Their Economic Impact. *HortScience*, *55*(5), 604–612. https://doi.org/10.21273/HORTSCI14696-19

Limayem, A., Martin, E. M., & Shankar, S. (2024). Study on the citrus greening disease: Current challenges and novel therapies. *Microbial Pathogenesis*, *192*, 106688. https://doi.org/10.1016/j.micpath.2024.106688

Liu, Y., Heying, E., & Tanumihardjo, S. A. (2012). History, Global Distribution, and Nutritional Importance of Citrus Fruits. *Comprehensive Reviews in Food Science and Food Safety*, *11*(6), 530–545. https://doi.org/10.1111/j.1541-4337.2012.00201.x

Lowenberg-DeBoer, J., & Erickson, B. (2019). Setting the Record Straight on Precision Agriculture Adoption. *Agronomy Journal*, *111*(4), 1552–1569. https://doi.org/10.2134/agronj2018.12.0779

Maldaner, L. F., Molin, J. P., & Spekken, M. (2022). Methodology to filter out outliers in high spatial density data to improve maps reliability. *Scientia Agricola*, *79*(1), e20200178. https://doi.org/10.1590/1678-992X-2020-0178

Mantoam, E. J., Romanelli, T. L., & Gimenez, L. M. (2016). Energy demand and greenhouse gases emissions in the life cycle of tractors. *Biosystems Engineering*, *151*, 158–170. https://doi.org/10.1016/j.biosystemseng.2016.08.028

Milan, M., & Rosa, J. H. M. (2015). Corte, transbordo e transporte (CTT): Aspectos relevantes e uso da modelagem para CTT. In *Processos agrícolas e mecanização da cana-de-açúcar*. Brazil, Luiz de Queiroz College of Agriculture, University of São Paulo.

Mira-García, A. B., Romero-Trigueros, C., Bayona, J. M., & Nicolás-Nicolás, E. (2024). Seasonal Dynamic of NO3− and K+ in a Citrus Crop Irrigated by Different Water Qualities. *Journal of Soil Science and Plant Nutrition*, *24*(3), 4269–4279. https://doi.org/10.1007/s42729-024-01832-8

Molin, J. P., Amaral, L. R., & Colaço, A. F. (2015). *Agricultura de precisão*. Brazil, Oficina de Textos.

Nawar, S., Corstanje, R., Halcro, G., Mulla, D., & Mouazen, A. M. (2017). Chapter Four - Delineation of Soil Management Zones for Variable-Rate Fertilization: A Review. In D. L. Sparks (Ed.), *Advances in Agronomy* (Vol. 143, pp. 175–245). Academic Press. https://doi.org/10.1016/bs.agron.2017.01.003

Ozkan, B., Akcaoz, H., & Karadeniz, F. (2004). Energy requirement and economic analysis of citrus production in Turkey. *Energy Conversion and Management*, *45*(11–12), 1821–1830. https://doi.org/10.1016/j.enconman.2003.10.002

Pellizzi, G. (1992). Use of energy and labour in Italian agriculture. *Journal of Agricultural Engineering Research*, *52*, 111–119. https://doi.org/10.1016/0021-8634(92)80054-V

Qin, W., Assinck, F. B. T., Heinen, M., & Oenema, O. (2016). Water and nitrogen use efficiencies in citrus production: A meta-analysis. *Agriculture, Ecosystems & Environment*, *222*, 103–111. https://doi.org/10.1016/j.agee.2016.01.052

Rasera, J. B., da Silva, R. F., Mourão Filho, F. de A. A., Delbem, A. C. B., Saraiva, A. M., Sentelhas, P. C., & Marques, P. A. A. (2023). Climate Change and Citriculture: A Bibliometric Analysis. *Agronomy*, *13*(3). https://doi.org/10.3390/agronomy13030723

Romanelli, T. L., & Milan, M. (2010). Material flow determination through agricultural machinery management. *Scientia Agricola*, *67*, 375–383. https://doi.org/10.1590/S0103-

90162010000400001

Soil Survey Staff. (2022). *Keys to soil taxonomy* (13th ed.). USDA Natural Resources Conservation Service. https://www.nrcs.usda.gov/sites/default/files/2022-09/Keys-to-Soil-Taxonomy.pdf

Späti, K., Huber, R., & Finger, R. (2021). Benefits of Increasing Information Accuracy in Variable Rate Technologies. *Ecological Economics*, *185*, 107047. https://doi.org/10.1016/j.ecolecon.2021.107047

Srivastava, A., & Das, S. (2017). Nutrient Optima-Based Productivity Zonality and Rationale of Fertilizer Use in Citrus (pp. 718–736). https://doi.org/10.9774/GLEAF.9781315365565_30

Tantalaki, N., Souravlas, S., & Roumeliotis, M. (2019). Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems. *Journal of Agricultural & Food Information*, *20*(4), 344–380. https://doi.org/10.1080/10496505.2019.1638264

Termin, D., Linker, R., Baram, S., Raveh, E., Ohana-Levi, N., & Paz-Kagan, T. (2023). Dynamic delineation of management zones for site-specific nitrogen fertilization in a citrus orchard. *Precision Agriculture*, *24*(4), 1570–1592. https://doi.org/10.1007/s11119-023-10008-w

van Raij, B., Cantarella, H., Quaggio, J. A., Furlani, A. M. C. (1997). Lime and fertilization prescriptions for the São Paulo State (Recomendações de adubação e calagem para o Estado de São Paulo). Technical book, Campinas, Brazil: IAC, 279p.

Wang, X., Qin, Y., Yang, Z., & Chen, X. (2026). Impacts of long-term planting on the microbial community of phosphorus mineralization in citrus orchard soil. *Journal of the Science of Food and Agriculture*, *106*(1), 675–684. https://doi.org/10.1002/jsfa.70198

Wei, M. C. F., Longchamps, L., Colaço, A. F., & Molin, J. P. (2026). Integrating stability zones and machine learning for enhanced crop management. *Precision Agriculture*, *27*(2), 38. https://doi.org/10.1007/s11119-026-10318-9

Xiong, H., Hu, B., Wang, J., Fu, X.-Z., Zhang, Y., Shi, X., & Rennenberg, H. (2025). Evergreen citrus trees exhibit distinct seasonal nitrogen remobilization patterns between mature leaves and bark. *Horticulture Research*, *12*(7), uhaf103. https://doi.org/10.1093/hr/uhaf103

Xu, H., Wang, Y. W., Luo, Z. W., Hu, W. L., Liao, W. Q., Chen, L. S., Li, Y., & Guo, J. X. (2024). Optimized nutrients management improved citrus yield and fruit quality in China: A meta-analysis. *The journal of applied ecology*, *35*(5), 1301–1311. https://doi.org/10.13287/j.1001-9332.202405.011

Zeng, T., Tong, J., Sun, X., Liu, J., He, X., Guan, Z., et al. (2025). YOLO-FCAP: An improved lightweight object detection model based on YOLOv8n for citrus yield prediction in complex environments. *Smart Agricultural Technology*, *12*, 101590. https://doi.org/10.1016/j.atech.2025.101590

Zeraatpisheh, M., Bakhshandeh, E., Emadi, M., Li, T., & Xu, M. (2020). Integration of PCA and Fuzzy Clustering for Delineation of Soil Management Zones and Cost-Efficiency Analysis in a Citrus Plantation. *Sustainability*, *12*(14). https://doi.org/10.3390/su12145809

Zhao, Y., Xiong, H., Luo, Y., Hu, B., Wang, J., Tang, X., et al. (2025). Long-term nitrogen fertilization alters the partitioning of amino acids between citrus leaves and fruits. *Frontiers in Plant Science*, Volume 15:1516000. https://doi.org/10.3389/fpls.2024.1516000