How to decide between buying or renovating agricultural tractors?

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Abstract

Deciding whether to buy or rebuild a tractor and when to do so is an empirical problem for farmers and/or rural administrators, whose analytical methods explored in the literature do not provide a clear approach to the operational and economic effects in the short and long term, despite its importance to the competitiveness of the activity. If the cost of replacing the agricultural tractors used in spraying the citrus crop could be more helpful than the reform of these, this study aimed to build and validate an economic evaluation method to support the decision to buy new or replace existing wheel tractors. To achieve such goals, a database with quarterly operational and financial information on 47 tractors between 2009 and 2017 was constructed. The method combined the use of an empirical, with the use of model panel-data regression, combining cross-sectional data with time series, to establish the actual cost information to be used in the model, and finally, implement the discounted cash flow, in which all uncertainties were controlled using a Monte Carlo simulation. The results indicated that the best decision is to purchase new equipment only after the fourth year of use. It stands out in the study findings, the impact of tax benefits and the resale of tractors were relevant to the cash flow, as well as the increase in maintenance costs over time. The economic evaluation method applied in this study can help rural producers and administrators in the decision-making process for investments in fixed assets and innovative technologies, thereby enabling them to be more accurate in their investment decisions. Technological progress increases the obsolescence rate of agricultural machinery and equipment whose paradigm referring to replacement was restricted to costs and operating conditions. In this study, it was found that the aggregate impact of expenditures and tax benefits had significant relevance on cash flow, therefore, should guide the analysis to create economic value.

Keywords: Valuation. Agricultural machinery. Investment decisions.

1. Introduction

The economic viability of rural properties that grow large-scale crops, such as soybeans, corn, sugarcane, and rice, is related to the increase in the number and the efficient use of agricultural machinery and implements (ALEM et al., 2018; GRANO; ABENSUR, 2017; CHANG et al., 2017; TIAN et al., 2019; YAGI; HAYASHI, 2020). In this context, agricultural tractors are prominent because they are the main equipment for soil tillage, material handling, and other operations whose contributions are related to the increase in the operational capacity and reduction of production costs (ZAJAC et al., 2017; AUNE et al., 2019; TAKESHIMA et al., 2020).

On the other hand, tractors and other similar agricultural machinery constitute the main capital expenditure (investment in fixed assets) for rural properties, however productive advances should not compromise the economic viability of the farm (SIMS; KIENZLE, 2015; ALEM et al., 2018; VAN LOON et al., 2020).

In recent decades, market professionals and academics have employed more sophisticated and assertive investment analysis techniques to assess the economic viability of the acquisition of new technologies in agriculture (RIMÉLÉ et al., 2018; HOLLAND, 2018; MELLICHAMP, 2018; RIMÉLÉ et al., 2020).

Traditionally, empirical studies on economic feasibility in agriculture, and those especially directed at agricultural implements and machines, have focused exclusively on the adoption of new technology through the acquisition of new equipment (GRANO; ABENSUR, 2017). However, there is a gap in the literature regarding (1) the ideal time when the producer should change the equipment and (2) the evolution of the operating costs of this equipment over time (AUNE et al., 2019; VAN DEN BOOMEN et al., 2019).

The greater use of machinery in the production environment requires greater investment in fixed assets, in fact, these assets assume a greater share in production costs, knowing the evolution of operating and maintenance costs of an agricultural machine over time is essential to build an investment analysis that allows decision making that adds value to the farm (ANDRADE et al., 2020). Maintenance and operating costs are expected to rise over time, given the wear and tear of the equipment, This fact has increased the importance of managing this process, in order to obtain the lowest possible cost of operating the production system (KHODABAKHSHIAN, 2013).

The literature on this aspect is based exclusively on the number of hours the machinery is used, that is, it assumes that a replacement occurs only when the total machinery wear or maintenance costs make it impracticable to continue using the machinery (KHODABAKHSHIAN, 2013; AUNE et al., 2019).

The exclusive use of operational information to decide when to renovate the machinery ignores the importance of investment decisions in a farm’s cash flow (RAHMAM; LATIFUNNAHAR; ALAM, 2013; VAN DEN BOOMEN et al., 2019). However, there is a difficulty in evaluating investment projects whose expected impact on cash flow is only cost reduction. This decision occurs, especially, in the comparison between machines in industrial and agricultural processes, the decision to renovate the machinery and equipment may not happen at the best time, from an economic point of view (HADRICH et al., 2013).

There is limited empirical information on the evolution of machinery maintenance and operational costs over time (SIMS; KIENZLE, 2015; HU et al., 2020). Moreover, the literature pays little attention to the option of investing in a broader renovation of existing machinery rather than purchasing new machinery (RAHMAM; LATIFUNNAHAR; ALAM, 2013).

The area cultivated with sweet orange in Brazil was 654.3 thousand hectares (ha) in the 2019/2020 forecast, for a tractor park of the order of 11 thousand machines. Approximately 424,800 ha of the total planting area are in the State of São Paulo (SPS) and the west-southwest of Minas Gerais, representing the most expressive citrus belt in Brazil (FUNDECITRUS, 2020; IBGE, 2020).

Considering that there are more than 1.2 million tractors in Brazil and that they are present in more than 737,000 rural properties (IBGE, 2017), there is a clear need to generate information and methods of economic valuation that may help farmers’ decision-making process. It is also believed that such an analysis would also draw the interest of other countries with a high degree of mechanization in their agricultural activities.

Currently, among the various methods for evaluating companies, the discounted cash flow (DCF) valuation continues to be the most widely used, both in academia and in the professional environment (COPIELLO, 2016; MCCARTHY et al., 2017; PRUSAK, 2017; AL-MUTAIRI et al., 2018; NIE, 2018; ALRASHED et al., 2020).

Rimélé et al. (2020) emphasized that although DCF is the most traditional method, its deterministic character limits the treatment of uncertainties in the cash flow projection. Boyer et al. (2018) and Rimélé et al. (2020) suggested the use of complementary stochastic tools for the analysis and the measurement of risks inherent to DCF.

According to Gleißner et al. (2017), Tsiboe et al. (2018), and Maia and Brandalise (2020), one of the alternatives for measuring the risk inherent in a company's valuation by DCFs consists of incorporating a Monte Carlo simulation into the conventional deterministic valuation model, thus creating a stochastic model that allows a statistical analysis of risk.

Given the scarce literature on the ideal time to renovate or purchase new agricultural equipment (RAHMAM; LATIFUNNAHAR; ALAM, 2013), and that the search for better margins and profitability led to an increase in the use of agricultural machinery, aiming at increasing the efficiency of operations and consequently reducing the cost of production. of renovating and purchasing new tractors, assuming that the cost of replacing the agricultural tractors used in spraying the citrus crop could be more advantageous than the reform of these.

In addition to contributing to the empirical study of an area that has been little explored in the literature, the proposed economic valuation model differs from the traditional approach of DCF as it incorporates a Monte Carlo simulation for cost variables and determines the evolution rate of tractors' operational costs over time.

2. Literature Review

Souza et al. (2020) highlight that agribusiness is undergoing a process of constant transformations, resulting in profound changes in management technologies and results assessment. Information on production costs and the economic viability of investments in agribusiness is often not clear or objective (AMORIM et al., 2018).

In this context, investment analysis and planning are essential for agricultural strategies, and it is of fundamental importance to be able to evaluate investments while they are still in the development phase (WYNN et al., 2019). Faleiros et al. (2018) highlight that the DCF together with the internal rate of return, the modified internal rate of return, and net present value (NPV) are widely used in empirical studies on investment in agrarian sciences.

Similarly, Frensidy et al. (2020), Mate and Occhino (2020), Rimélé et al. (2018), Prusak (2017), and Nie (2018) highlight that the DCF method is the most used model for investment evaluation. Dadteev et al. (2020) argue that this method is one of the most important concepts in financial analysis applied in the agriculture context.

The importance of cash flow-based economic analysis to support rural producer decisions lies in its ability to evaluate decisions as a function of the effect on cash, considering variables related to time and risk (FALEIROS et al., 2018). This result opposes the exclusive use of productive indicators, considering that the expenses to increase productivity levels or minimize losses may have different variations; therefore, it is possible to identify an increase in operating performance associated with an increase in negative financial results (RAHMAM; LATIFUNNAHAR; ALAM, 2013).

Considering the above, the DCF, which represents the present value of future cash flows, can be calculated using Equation (1) (DAMODARAN, 2012):

$$DCF = \frac{\sum_{j=1}^{t} FCF_j}{(1+k)^t}, \tag{1}$$

where FCF is the free cash flow, k is the minimum attractive rate of return, and t is time.

According to Damodaran (2012), the minimum attractiveness rate is the rate at which the owner/investor is remunerated for his/her investment. Its traditional calculation methodology involves the asset pricing model, shown in Equation 2:

$$k = R_f + \beta_i(R_m - R_f), \tag{2}$$

where Rf = risk-free asset return (in this case, the CDI was used), β = beta of the asset, that is, the regression coefficient for the difference between the asset of interest and the market asset, and Rm = return on the asset that expresses the market portfolio.

Armitage (2008) presents the determinants incorporated into the DCF, based on incremental cost. Al-Suhaibani and Wahby (2017) comment that in the case of agricultural tractors, the systematic monitoring of their performance and the calculation of the operating costs throughout their useful lifetimes are fundamental factors for their rational use.

The authors also argue that mechanized methods have acquisition costs that, at first sight, may be prohibitive for small farmers. However, if a cost analysis of the impacts of mechanization on the production chain becomes available, it will show the advantages of adopting more modern systems (AL-SUHAIBANI; WAHBY, 2017).

Faleiros et al. (2020) and Barbosa and Gimenes (2020) show that an adequate cost analysis for an investment helps the farmer’s decision-making, mainly in the DCF evaluation. It is noteworthy that the analysis of investments to replace assets is not usual in empirical studies, but it was possible to identify studies that used the DCF to verify support the decision between renewing or buying a new asset, such as: Immergluck and Law (2014), Alessandrini et al. (2017) and Sampaio et al. (2019). In these studies, the assessment by the DCF is based on the difference in costs between refurbished and new assets. As costs negatively impact the farmer's cash flow, the decision is always based on the alternative that confers the least negative impact on the rural property.

It should be noted that, when the decision is directed towards a choice between acquiring new equipment or renovating it, the selection criteria must consider: differences in operational efficiency; ii) difference in operating costs; iii) differences in investment values; and iv) differences in residual values. According to Pacheco (2000), the renovation of machinery is an important decision and is related to the cost of using the machines; however, there is no theoretical discussion based on empirical evidence about the ideal time to replace the equipment so that the investment is fully recovered and still allows for an economic return to the owner.

This gap in the literature presented by Pacheco (2000), who demonstrates the evolution of the operating costs of tractors, relating market information to the costs of refurbished tractors, is explored in depth in this work.

2.1. Empirical Model

The scope of this study resides in the analysis between the complete replace of a tractor (engine, hydraulic and electrical systems and tires) of a tractor or the purchase of a machine of the same model. As there is no operational difference between the tractors, the effects on operational efficiency are null.

Thus, the main differences in values are in operating costs related to maintenance, investment values and residual value of tractors, and for these there is no evidence in the literature regarding their evolution over time (HE et al., 2008).

2.1.1. Operating Costs

The operating costs of an agricultural machine include: operating labor, predictive maintenance, preventive maintenance, corrective maintenance, fuel, lubricants/oil and other inputs of lesser financial relevance such as sanitation (KHODABAKHSHIAN, 2013).

The differences in operating costs are related to maintenance (predictive, preventive and corrective), fuel and lubricants/oil. According to the literature, these are the main operating costs inherent to the full availability of the equipment (He et al., 2008; ANDRADE et al., 2020); and the total operating cost (OC) per hour worked can be represented by Equation 1:

$$\frac{OC_{it}}{h} = \frac{Lub_{it}}{h} + \frac{Mai}{h} + \frac{Lab_{it}}{h} + \frac{Fue_{it}}{h} \quad (01)$$

Onde:

Lub – Lubricants and oil

Mai - Mainteance

Lab – Labor

Fue – Fuel

h – hours

i – i-esimo tractor

t – time

It is noted in equation 1 that all variables are relativized by the hour worked, which is one of the main measures of use and efficiency of the tractor and serves as a 'standardization' factor for the variables, however, as will be shown, there is a variation in training of each element, which requires an empirical model to estimate the coefficients of each of these factors (KHODABAKHSHIAN, 2013).

The volume of hours has a positive relationship with fuel and lubricant cost variables, considering that they are inputs directly related to the operation of the equipment (CALCANTE et al., 2019; ANDRADE et al., 2020). However, empirical studies show that factors external to tractor operation influence fuel and lubricant consumption, such as operator skill level, soil conditions and weather (RAHMAM; LATIFUNNAHA;, ALAM, 2013). These environmental conditions can be isolated in controlled experiments, but not in real situations, where farms have different operators, with different skill levels, weather and traffic conditions in the areas change frequently and impact each machine in different ways, due to heterogeneity of service orders (CALCANTE et al., 2019). Thus, even though there is a direct relationship between hours worked and the consumption of lubricants and fuel, this coefficient may show variability, as reported by He et al. (2008) and Calcante et al. (2019).

Maintenance cost also has a positive causal relationship with the hours worked, according to Khodabakhshian (2013). However, this relationship is less predictable than the fuel and lubricant variables. Empirical reports demonstrate that it is not possible to accurately determine the financial impact of these maintenances with the volume of hours. This difficulty arises for different reasons, such as: defects in the manufacturing process; possible variations in the strength of the materials and components used; maintenance service execution; availability of maintenance parts, among other exogenous factors that influence the variation in the cost of maintenance and the time to perform it, which in turn impacts the unavailability of the equipment and the amount of hours worked by the equipment in a given period (KHODABAKHSHIAN, 2013).

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A similar analysis of the maintenance cost is the cost of labor for this service. Although Khodabakhshian (2013) points out that machines with a higher level of use will require a higher level of maintenance labor services, this relationship is not so direct; as there is a heterogeneity of maintenance services for tractors that consume different times to be performed and are also influenced by behavioral factors of the professional and the different levels of skills they present. Empirical evidence demonstrates that there is no single, known cost relation that manifests itself equally at all times in maintenance services (HE et al., 2008).

It is also known that the longer the use of machines and equipment, the higher the costs inherent to maintenance tend to be, and even though the hours worked have a direct impact on the wear and consumption of tractor inputs, the course of time, only, it is also a factor of natural wear of machine parts and components, especially agricultural ones that are directly exposed to bad weather.

It is noted, therefore, that despite the OC being formed by the costs of maintenance, fuel and lubricants, these costs can vary from tractor to tractor and at each moment, which makes it necessary to find coefficients of variation that more accurately estimate the 'average' impact of each variable on the total cost, as well as the temporal effect.

It is noteworthy that the tractors analyzed in this study are used only in the spraying activity, considering that the characteristics of agricultural implements imply differences in tractor power and effort (ESAU et al., 2016).

Thus, Equation 2 was proposed to estimate the coefficient of variation of each factor of the total operating cost and the effects on time.

$$OC_{it} = \alpha_i + \beta_1 \mathrm{Lub}_{it} + \beta_2 Mai_{it} + \beta_3 Lab_{it} + \beta_4 Fue_{it} + \beta_5 Q1_{it} + \cdots + \beta_{13} Q11_{it} + \varepsilon_{i,t} \quad (02)$$

where OC is the total cost per hour worked, Lub is the cost per lubricant per hour worked, Mai is the maintenance cost, Lab is the cost of labor dedicated to maintenance, Fue is the fuel cost and the variables Q1 to Q11 are dummy temporal variables to control the effect of time on cost evolution. For this study, it was possible to build a database with quarterly information for 4 years and, therefore, the indication of the letter Q, ε is the random error term, *i* represents each tractor unit, and *t* at each time.

The use of regression to estimate cost coefficients is not new in the literature (HE et al., 2008; CALCANTE et al., 2019). However, the use of a regression model with panel data for maintenance of agricultural machinery and equipment was not identified to identify not only the impact coefficients on the total cost, but also its evolution over time. As this study requires the forecast of the evolution of costs over time of different machines, it is necessary to estimate the evolution of costs of each machine for comparison purposes.

The distinct impacts on the rural property's cash flow from each of the alternatives are reflected in the rural property's taxable income, so the tax benefits need to be considered. In addition, the temporal impact of operating costs must be identified, as the mechanical, hydraulic and electrical wear of agricultural machines tends to increase with time of use, although there is little information on this fact in the literature (KHODABAKHSHIAN, 2013).

Thus, after estimating the operating costs between the two machines, their respective investments and taxable effects, it will be possible to realize the economic impact of each machine on the rural property and its incremental cash flow.

Among these techniques, the panel-data regression model is a prominent one (GUJARATI; PORTER, 2009; HAIR et al., 2016). In recent decades, there has been a rapid development of analysis methods and techniques based on the use of panel data (HENNINGSEN; HENNINGSEN, 2019). The empirical model used in this research is based on Equation 3:

Henningsen and Henningsen (2019) demonstrate the application of several panel data estimators frequently used in social scientific analyses. Gil-García et al. (2014) used the aforementioned model in quantitative analysis courses in higher education programs worldwide. Takeshima et al. (2020) used panel data to obtain information on the costs of agricultural mechanization in Nigeria.

In the model presented in Equation 3, some variables may contain high levels of uncertainty. Liu et al. (2020) consider the problem of predicting short time series using transversal information in panel data through Monte Carlo simulations. Leszczensky and Wolbring (2019) show how to use casualized data in conditions of uncertainty using Monte Carlo simulation with panel data. Khalfi and Ourbih-Tari (2019) discuss how to mitigate risk through Monte Carlo simulations.

Monte Carlo simulation is a tool used to calculate the probability of a specific event (SHAKIR, 2019). It is a technique that uses random numbers, which are generated within a probabilistic distribution model with lower and upper limits for an uncertain variable (AHMED et al., 2020).

Khalfi and Ourbih-Tari (2019) argue that it is a technique that allows the evaluation of all the possible values of a given variable, being the best way to quantitatively analyze the risk pertinent to this variable.

3. Materials and Methods

According to Gil (1999), this research has an applied nature, with an exploratory purpose, as it seeks, together with the empirical reality, the evaluation of the economic viability of replacing tire tractors used in the spraying of Citrus crops. The procedure used in the research consists of a case study, with a quantitative nature, as it seeks to examine a contemporary phenomenon within the context in which it is found, through a database and econometric methods (YIN 2004).

The study was conducted in a citrus-producing agricultural company located in Matão, SP, Brazil, near the geodesic coordinates 21°3715″ S and 48°2639″ W, with an altitude ranging from 590 to 615 m, an area of 10,000 hectares, and 2.5 million citrus plants. The machinery park consisted of 115 agricultural machines, 90% of which were wheeled tractors of 70 to 100 hp, used for spraying the citrus crop.

Simulations were performed for each component of the tractor unit cost (lubricant, maintenance, fuel, and labor) for the period between May 2009 and April 2017 to increase the reliability of the analysis. All values were updated using the official Brazilian inflation index for June 2018. Data from 47 tractors were used in this study.

To obtain and collect data, primary and secondary data were used. Primary data were obtained from observations and interviews with managers of each department. Secondary data were collected through the researcher during weekly site visits, which took place between May and September 2018. The documents of the maintenance team were evaluated, so it was possible to check information on the consumption of fuel and lubricants, maintenance hours, as well as individual hours of use per tractor.

The data were collected based on the utilization history and were compiled quarterly, through spreadsheets, from the date of the beginning of the use of each tractor until its scrapping or sale, that is, the end of its useful lifetime.

The data show the real evolution of the operational costs of the machines, based on a robust database, with detailed information on the costs and specificities of the evaluated machines. Table I shows the main characteristics of the evaluated tractors.

Table I: Technical characteristics of the used tractors.

Group	Quantity	Brand*	Model	Power**	Traction	Cabin	Year
A	20	JD	5078E	57,4/78	4x2 FWD	Yes	2014
B	17	MF	4283	63,5/85	4x2 FWD	Yes	2011
C	10	MF	283	63,5/85	4x2 FWD	Yes	2009

*JD: John Deere; MF: Massey Ferguson. **Power in kW/hp.
Source: John Deere (2019) and Massey Ferguson (2019).

The present study is unique in its use of data on the costs of the equipment measured in a real context of operation and not in an experiment in which the operating conditions are "controlled.”

The regional climate was considered subtropical, classified as Cwa by the Köppen method, as presented by Naranjo et al. (2018), and characterized by two well-defined seasons (warm and humid summer and cold and dry winter). The main soil types were Ultisol, Oxisol, and Entisol, with medium to clay texture, and being predominantly eutrophic.

Two different scenarios were evaluated in this study:

Scenario I: Replacement of existing equipment with new equipment.

Scenario II: Partial renovation (engine, transmission, electrical system, and tires) of equipment to recover it to its original working condition.

Regression analysis with panel data was used in order to identify the estimators of each variable that forms the cost of a machine. A panel-data regression model, using real cost information available in the studied environment, was adopted as a method to establish the cost evolution parameters applied to a new machine (Figure 1).

A panel-data regression analysis was the best methodological alternative for this study because of its potential to combine cross-sectional data with time series (GRILL, 2017), increasing the number of observations and allowing the extraction of information by moderating the effect of time. This is necessary because this study aims to measure the extent of the increase in operational costs as a tractor ages.

The empirical model used in this research has its identity in Equation 3:

$$Y_{i,t} = \beta_1 X1_{i,t} + \beta_2 X2_{i,t} + \beta_3 X3_{i,t} + \beta_4 X4_{i,t} + \beta_5 X5_{i,t} + \cdots + \beta_{13} X13_{i,t} + \varepsilon_{i,t} \quad (03)$$

Where: Y is the Total Unit Cost, X1 is the Unit Cost of Lubricant, X2 represents the Unit Cost of Maintenance, X3 is the Unit Cost of Labor (own and outsourced), X4 is the Unit Cost of Fuel and X5 to X13 are temporal dummy variables, ε represents the random error term, i represents the ith tractor and t is the temporal variable.

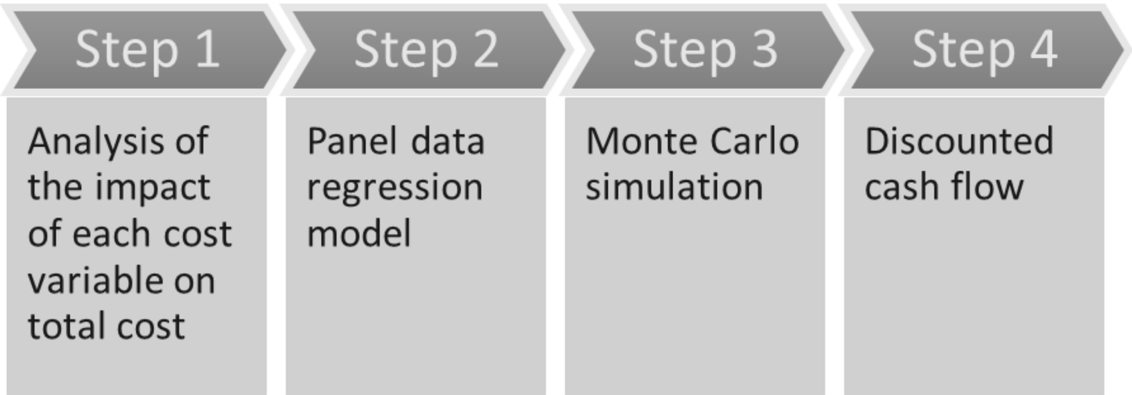

Figure 1: Flow of steps followed in this research.

The technique used in this study was fixed-effects weighted least squares (WLS). Fixed-effects were chosen because the sample comprised three different machinery models. Thus, there is a difference between models and manufacturers, and, hence, the results cannot be assumed to be random (BELL et al., 2019). Heteroscedasticity was detected when ordinary least squares were used, which means that the variables do not show a uniform distribution of variance over time and between models. Therefore, WLS were chosen to correct this issue

(GUJARATI; PORTER, 2009; HAIR et al., 2016).

All the machinery costs in each quarter were normalized based on the number of use hours of each piece of equipment. The adjusted R^2 and R^2 and the F-statistics were used for model specification to verify the model fit tests (GUJARATI; PORTER, 2009).

Therefore, this study proposes the use of the incremental cash flow to be generated by the cash flows of new and renovated machinery. Because this study aims to propose a method to aid the decision of whether to purchase or renovate a tractor, an exclusionary analysis of investments is performed, in which the decision-maker must decide on one or another project (GASPARS-WIELOCH, 2019).

The calculation considered the annual depreciation rate of wheeled tractors of 25% accepted by the Federal Revenue of Brazil, which allows the full depreciation of the machinery in four years and the use of a tax benefit. The income tax and social contribution rate were the same for the studied company (34%).

Cash flow is composed of discrete values, which makes it challenging to control for uncertainties; only the rate is considered as a risk factor (MINTAH et al., 2018). Because of this limitation, the Monte Carlo simulation method was used to control for the uncertainties in all cost variables, as presented by Boyer et al. (2018), Gleißner et al. (2017), and Maia and Brandalise (2020).

The Monte Carlo simulation was structured. For this, the average costs of each tractor model were used for each period. The values of investment, renovation, resale, and depreciation were not simulated because they are known. The Monte Carlo simulation in the DCF was used to control for the differences in the results among the machines so that the economic evaluation would not involve a discrete, but a continuous structure (BOYER et al., 2018).

4. Results and Discussion

Table II shows the descriptive statistics of the variables used to discriminate the direct costs of the sample. The results are normalized by each machine's use hours.

Fuel cost (US$ 3.77 per hour) accounted for 67.7% of the total direct cost of the 47 tractors; however, the workforce cost for their operation was almost three times higher than the second most relevant cost, maintenance.

These results indicate the importance of machinery operational control in the fuel consumption level, as well as the need for technological advances in the use of more efficient engines and/or cheaper energy sources, such as Emami (2018).

Starting in 2019, tractor models with power equal to or exceeding 19 kW (25 hp) and up to 75 kW (101 hp) must comply with the new legislation of the Brazilian Program for Control of Air Pollution by Motor Vehicles (PROCONVE)—MAR-1, which defines emission limits for carbon monoxide, hydrocarbons, nitrogen oxides, and particulate matter. For this reason, new technologies embedded in low-power engines are expected to emerge from 2019, leading to an improvement in performance and, consequently, the possibility of reducing fuel consumption (EMAMI, 2018).

The coefficient of variation shows that the cost associated with fuel consumption provides the lowest dispersion level, indicating that the individual results are dispersed closer to the mean, although the data include cross-sectional information from the 47 tractors during 12 quarters. This higher linearity of fuel consumption is reflected in the correlation coefficient with the total cost, which was significant (HAIR et al., 2016). This result is interesting as it demonstrates that, despite the diversity of factors that may be related to the variability of fuel consumption, such as the operators' behavioral aspects, the small dispersion reflects the low influence of these factors and, consequently, the rather uniform cost of the machinery.

Maintenance and workforce costs used in maintenance activities (Table II) represent 27.9% of the unit cost, reaching a mean value of US$ 1.55 per hour. Although these are lower than the fuel cost, these variables are representative of the total cost. The degree of correlation between these two variables is significant, which indicates that the volatility of the total cost is directly associated with the volatility of the maintenance and workforce costs, confirming the findings of Al-Suhaibani and Wahby (2017).

Table II: Descriptive results of the variables of payable costs of tractors per hour.

				Correlation coefficient				
Variable	Mean (US$/hour)	SD†	CV	Lubricant cost	Maintenance cost	Workforce cost	Fuel cost	Total cost
Lubricant	0.23	0.12	0.13	1.00	0.28**	0.20**	0.29**	0.41**
Maintenance	1.22	1.63	0.33		1.00	0.73**	0.10*	0.91**
Workforce	0.33	0.47	0.35			1.00	−0.02	0.73**
Fuel	3.77	0.88	0.06				1.00	0.46**
Total cost	5.57	2.29	0.10					1.00

†SD = Standard deviation; CV = Coefficient of variation. *Significant at 0.05; **Significant at 0.01.

Lubricant costs (Table II) represent the lowest direct cost for a tractor, and their correlation with the total cost is weak, which corroborates the empirical evidence, as they are associated with preventive maintenance, whose accomplishment has a weak association with the other variables.

Except for the absence of correlation between fuel and workforce, all other explanatory variables of the total unit cost exhibited positive and significant correlations. However, these were weak for all the variables but were reasonable for workforce and maintenance, which was already expected. The weak correlations are relevant because they limit the effects of multicollinearity, although the latter cannot be excluded, due to its significance (GUJARATI; PORTER, 2009). The absence of a correlation between fuel and workforce demonstrates the effect of adequate operator training, which minimizes the variety of factors that could increase fuel consumption by different operators, such as the choice of gears and improper rotations.

Table III shows the results of the panel-data regression model using the WLS technique. The latter was used to correct for the presence of heteroscedasticity, as presented by Tsega et al. (2018). Because there are results of 47 machines operating in 12 quarters, the total observations used in the model were 564.

The model had 15 variables, 4 of which referred to the cost elements of a tractor that constitute the total machinery cost (Table III), while the other 11 were used to control for the effect of time on the total cost.

Table III. Results of the panel data regression analysis consider as dependent variable the total unit cost.

Variable	Coefficient	Standard error	Confidence interval
Lubricant unit cost	0.028**	0.007	(0.012, 0.044)
Maintenance unit cost	0.173**	0.006	(0.161, 0.184)
Workforce unit cost	0.071**	0.005	(0.060, 0.082)
Fuel unit cost	1.033**	0.005	(1.021, 1.045)
dt 1	0.238**	0.021	(0.195, 0.281)
dt 2	0.170**	0.020	(0.130, 0.211)
dt 3	0.096**	0.019	(0.058, 0.135)
dt 4	0.089**	0.019	(0.050, 0.129)
dt 5	0.099**	0.019	(0.061, 0.137)
dt 6	0.057**	0.019	(0.019, 0.095)
dt 7	0.059**	0.019	(0.021, 0.097)
dt 8	0.062**	0.019	(0.024, 0.100)
dt 9	0.038*	0.019	(0.000, 0.075)
dt 10	0.047*	0.019	(0.009, 0.085)
dt 11	0.034*	0.019	(−0.003, 0.072)
Sum of squared residuals	507.7	Adjusted R^2	0.887
R^2	0.992	F (15, 546)	287.219
Standard error of regression	0.964	P-value (F-stat)	0.000

*Significant at 0.05; **Significant at 0.01.

The natural logarithm of the unit cost variables was used for a better model fit, by minimizing the differences in variance among the variables (HAIR et al., 2016).

The model presented an adequate fit, as the coefficients of determination R^2 and adjusted R^2 were high and had similar values as presented by Gujarati and Porter (2009). Nevertheless, the F test rejects the null hypothesis, indicating a poor model specification (Table III).

However, the model shown in Table III does not utilize a constant so all regression straight lines pass through the origin (HAIR et al., 2016). For each estimator, 95% confidence intervals were used, to increase the reliability of the estimator (HAIR et al., 2016). The amplitude between the minimum and maximum values is relatively small for all variables and, therefore, the values are close to the partial regression coefficients.

All coefficients of unit cost were positive for the log-transformed variables (Table III), and can be presented in decreasing order of relevance as follows: fuel unit cost (1.033), maintenance unit cost (0.173), labor unit cost (0.071), and lubricant unit cost (0.028). The order of importance of these results agrees with the mean values shown in Table II, which increases the confidence in these results, supporting the findings of Al-Suhaibani and Wahby (2017).

Because the independent variables of the models showed significant correlation coefficients (except for workforce and fuel), multicollinearity may exist, which limits the accuracy of the regression analysis for estimation purposes (GIACALONE et al., 2018) because part of the variance of each variable may be influenced and superimposed on the variance of other variables.

The coefficients of the control variables (dummies) for the impact of time on costs were significant and positive, thus confirming the empirical evidence that time has an entropic impact on systems, causing higher wear levels and, consequently, in this case, a higher impact on variable costs, which strengthens the evidence presented by Gitau et al. (2018). However, the growth rate of the coefficients of the time variables is negative, that is, the coefficients are positive over time, but their values decrease over time. The highest values and variation rates occur in the first years because they are based on a new machine, whose corrective maintenance cost is practically null in its first year of work. Further, in the first year, we have the preventive maintenance of the new tractor.

Time control variables, in addition to showing the nominal cost growth, allowed the estimation of the mean growth rate of the costs of a tractor over time (Figure 2).

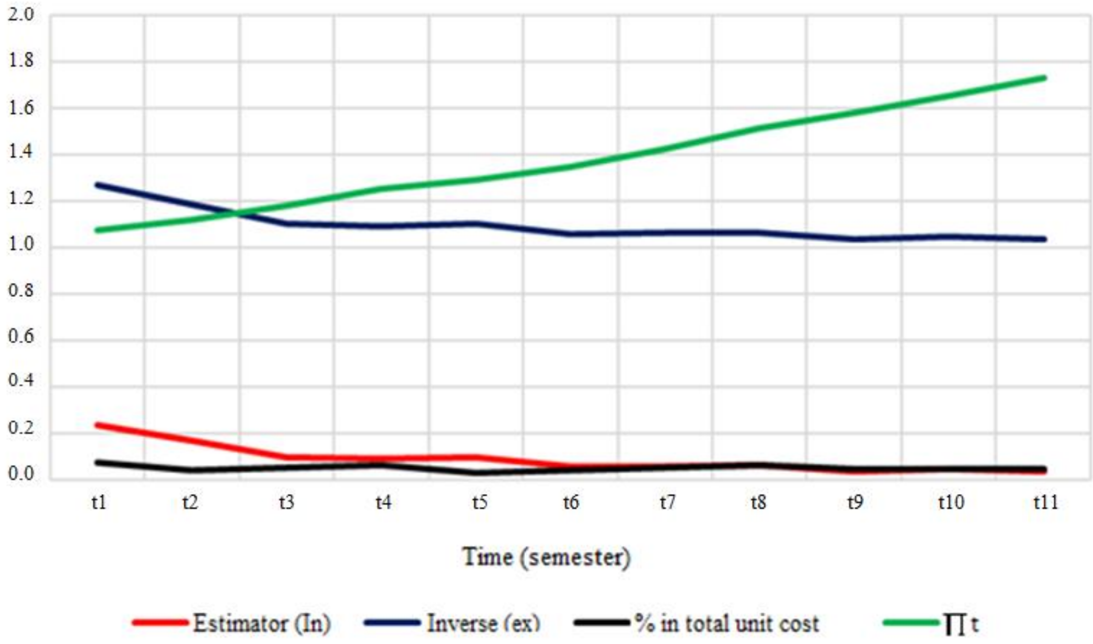

Figure 2: Estimation of the mean growth rate of the costs of a tractor over time.

Thus, total nominal growth of 73% is observed in the analyzed quarters. Considering inflation of 30% in the analyzed period, the real growth rate of costs is equivalent to 5.36% semiannually or 2.65% quarterly, considering compound interest.

Although the model allowed identifying the cost growth process over time and the impact of each variable on the total cost, the model did not provide information on the decision of replacing the equipment or renovating them. Thus, the financial analysis of these variables for decision-making needs to be extended to investment analysis models that consider the effect of these costs on the company cash flow, which is, ultimately, the result that determines the solvency and value of the investment, as exposed by Coelho (2016).

The DCF structure was examined for the financial analysis, being projected for eight semesters (four years) for tractors of groups A and B and ten semesters (five years) for group C. This period was defined based on the legal possibility of fully depreciating the tractor within four years, which accelerates the tax benefit of deductibility of the income tax and social contribution.

The company is taxed under the regime known in Brazil as real profit when the tax is calculated on the income deducted from operating costs and expenses. Accordingly, the income tax is 24% plus 10% when the LAIR exceeds R$ 240,000.00 by the Corporate Income Tax Regulation (IRPJ), Law No. 9,430, of December 27, 1996.

Further, the variable t8 (corresponding to the fourth semester) showed a growth in the estimator when compared to the previous period, which indicates that in addition to the cost growth (positive estimator), the rate of change is also positive (Figure 2).

Because the original data are related to new machinery (scenario I), the proposed scenario II presents the challenge of establishing the evolution of the maintenance cost of a partially renovated machine during its use. The reason is that no studies are addressing the subject and the company does not have these data because it does not renovate the equipment, but, instead, replace them. Thus, a rate of 5.36% per semester was used as a proxy for cost evolution during the useful lifetime of the machinery.

Table II shows the dispersion around the mean results of the cost variables. A Monte Carlo simulation with the provision of 10,000 possible values for each financial cost variable for each semester was used to make the investment analysis more robust (SHAKIR, 2019). Because cost values are financial and operational costs/expenses cannot be negative, the Monte Carlo simulation was performed considering a discrete distribution for each variable.

The minimum and maximum values of the cost variables for the machinery from the studied tractor groups A, B, and C in each period, which allowed analyzing the DCF through the Monte Carlo simulation, as in Boyer et al. (2018), are presented in the supplementary materials.

Table IV shows the mean results in the cash flow structure of the 10,000 simulations for scenarios I and II for group A tractors. The results for other groups can be found in the supplementary materials.

The discount rate was set at 5.09% using the capital asset pricing model (CAPM) technique, as presented in Damodaran (2012). The assumptions for the calculation were as follows: a risk-free asset of the Brazilian Bond of 6.39% (May/2018), a beta of 0.47, and a market risk premium of 6% per year. Beta was determined based on the mean of the last 36 months (September 2015 to September 2018) of agricultural companies listed on the Brazilian Stock Exchange (B3).

Table IV: Mean results in a cash flow structure of 10,000 simulations for scenarios I and II for tractors of group A (US$).

Scenario I - Replacement of obsolete equipment with a new one														
Costs†		1st sem.	2nd sem.	3rd sem.	4th sem.	5th sem.	6th sem.	7th sem.	8th sem.	9th sem.	10th sem.	11th sem.	12th sem.	13th s
Lubricant cost		1.42	1.63	1.87	1.65	1.78	1.82	2.27	2.17	1.42	1.65	1.87	1.65	1.77
Maintenance cost		2.48	4.60	12.72	8.97	7.23	17.23	12.15	8.22	2.46	4.59	12.61	9.06	7.19
Main workforce cost		0.34	0.94	1.20	2.20	1.39	2.50	1.79	0.94	0.35	0.93	1.20	2.18	1.39
Outsourced workforce cost		0.86	0.85	1.17	2.59	2.25	1.27	1.84	2.47	0.86	0.85	1.17	2.61	2.23
Fuel cost		23.32	33.66	33.89	25.97	30.98	28.77	31.99	25.88	23.37	33.73	34.09	26.00	31.00
Depreciation cost		11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60
Total		40.01	53.28	62.45	52.97	55.23	63.18	61.62	51.27	40.05	53.35	62.54	53.09	55.18
Income tax/SC (tax benefit)		13.60	18.12	21.23	18.01	18.78	21.48	20.95	17.43	13.62	18.14	21.26	18.05	18.76
Outcome		26.41	35.16	41.22	34.96	36.45	41.70	40.67	33.84	26.44	35.21	41.28	35.04	36.42
Depreciation (credit)		11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60
OCF		−14.81	−23.57	−29.62	−23.37	−24.86	−30.11	−29.08	−22.24	−14.84	−23.62	−29.68	−23.44	−24.8
Divestment									34.18					
Investment	92.76								92.76					
FCF	−92.76	−14.81	−23.57	−29.62	−23.37	−24.86	−30.11	−29.08	−80.82	−14.84	−23.62	−29.68	−23.44	−24.
NPV	−438.47													
FCFE	−33.62													
NPV/machinery	−21.92													
Scenario II - Partial renovation (motor, transmission, electrical system, and tires) of obsolete equipment to recover their original working conditions														
Costs		1st sem.	2nd sem.	3rd sem.	4th sem.	5th sem.	6th sem.	7th sem.	8th sem.	9th sem.	10th sem.	11th sem.	12th sem.	13th s
Lubricant cost		1.41	1.65	1.88	1.65	1.77	1.82	2.27	2.17	1.55	1.78	2.04	1.78	2.01
Maintenance cost		2.46	4.58	12.67	9.05	7.23	17.31	12.17	8.21	2.66	4.97	13.71	9.73	7.81
Main workforce cost		0.34	0.93	1.20	2.19	1.40	2.50	1.78	0.94	0.37	1.01	1.29	2.34	1.49
Outsourced workforce cost		0.86	0.85	1.18	2.61	2.26	1.27	1.86	2.47	0.93	0.92	1.28	2.84	2.42
Fuel cost		23.34	33.64	34.05	25.96	30.99	28.72	32.05	25.95	25.20	36.45	36.72	28.07	33.53
Depreciation cost		11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	5.89	5.89	5.89	5.89	5.89
Total		40.00	53.25	62.58	53.05	55.24	63.21	61.72	51.33	36.59	51.01	60.93	50.65	53.16
Income tax/SC (tax benefit)		13.60	18.11	21.28	18.04	18.78	21.49	20.99	17.45	12.44	17.35	20.72	17.22	18.07
Outcome		26.40	35.15	41.30	35.01	36.46	41.72	40.74	33.88	24.15	33.67	40.22	33.42	35.08
Depreciation (credit)		11.60	11.60	11.60	11.60	11.60	11.60	11.60	11.60	5.89	5.89	5.89	5.89	5.89
OCF		−14.81	−23.55	−29.71	−23.42	−24.86	−30.13	−29.14	−22.28	−18.26	−27.78	−34.33	−27.54	−29.2
Divestment														
Investment	92.76								47.09					
FCF	−92.76	−14.81	−23.55	−29.71	−23.42	−24.86	−30.13	−29.14	−69.37	−18.26	−27.78	−34.33	−27.54	−29.2
NPV	−464.68													
FCFE	−35.63													
CFI	2.01													
INPV	26.21													
NPV/ machinery	−23.23													
INPV/ machinery	1.31													

†FCFE, Free Cash Flow to Equity; CFI, Cash Flow from Investing Activities; FCF, Free Cash Flow; OCF, Operating Cash Flow; NPV, Net Present Value; INPV, Incremental Net Present Value.

The stratified analysis of the performance of each cost element is shown in Table 5. Economically, we will have financial disbursement in both scenarios presented through the DCF. Between scenario I, which has an FCF of US$ - 345,706, and scenario II, which presents an FCF of US$ -371,917 for Group A, representing an incremental value of US$ 26,211, the most economical option is the scenario I.

The best decision for all groups of tractors is the scenario I (replacement of machinery) because the result is positive for the difference in FCF, with values US$ 26,211, 36,302, and 29,789 for groups A, B, and C, respectively, as shown in the last row of Table V.

Thus, all groups presented a positive incremental NPV for replacement.

The cost variables in the scenario I in the three groups of tractors exhibited lower values compared with those of the cost variables in scenario II. Therefore, the incremental cash flow is positive because the costs inherent to the scenario I (replacement of machinery) were lower when compared with those of scenario II (partial renovation of machinery).

Table V: Stratified analysis of the performance of each cost element (US$).

Brand/model	**Group A**			**Group B**			**Group C**		
Proposed scenario†	**Scenario I**	**Scenario II**	**Difference**	**Scenario I**	**Scenario II**	**Difference**	**Scenario I**	**Scenario II**	**Difference**
Lubricant cost	23,646	24,621	−976	25,528	26,688	−1,160	30,219	31,544	−1,326
Maintenance cost	118,014	122,400	−4,387	126,991	132,505	−5,514	147,439	154,223	−6,784
Main workforce cost	18,176	18,791	−614,000	27,046	28,261	−1,216	33,805	35,417	−1,612
Outsourced workforce cost	21,350	22,230	−880,000	17,524	18,240	−716,000	32,525	34,891	−2,367
Fuel cost	382,567	396,587	−14,020	374,829	391,562	−16,733	362,746	378,598	−15,852
Depreciation cost	151,225	117,678	33,547	185,519	139,846	45,674	151,225	117,678	33,547
Total	714,978	702,308	12,670	757,437	737,103	20,334	754,660	750,677	3,983
Income tax/SC (tax benefit)	243,092	238,785	4,308	257,529	250,615	6,914	256,585	255,230	1,354
Outcome	471,885	463,523	8,362	499,909	486,488	13,421	498,076	495,447	2,629
Depreciation (credit)	151,225	117,678	33,547	185,519	139,846	45,674	147,927	116,004	31,923
OCF	−320,660	−345,845	25,185	−314,389	−346,642	32,253	−350,149	−379,443	29,294
Divestment	65,876	18,189	47,687	68,369	18,646	49,723	65,876	18,189	47,687
Investment	90,486	45,932	44,554	92,760	47,086	45,674	90,486	45,932	44,554
FCF	−345,706	−371,917	26,211	−338,780	−375,082	36,302	−375,041	−404,831	29,789

†FCF, Free Cash Flow; OCF, Operating Cash Flow.

Table V also shows that depreciation was the only variable unfavorable to the replacement of all the tractor groups, which is natural because tractor replacement means a higher flow of investment. Moreover, the total cost analysis shows that this value is unfavorable for replacement because it exhibits a cost of US$ 12,670 for group A, and US$ 20,334 and US$ 3,983 for groups B and C, respectively when compared with renovation.

However, this analysis must be extended as there is a tax benefit of US$ 4,308 (Group A), US$ 6,914 (Group B), and US$ 1,354 (Group C) in favor of replacement. Because depreciation is not a financial cost, it does not impact the cash flow, only the investment and when it is made. In this sense, the impacts of investment and divestment on cash flow are important. Because during two cycles of four or five years, the replacement decision will involve the sale of tractors with four or five years of use, the divestment value is higher for the replacement option, both due to the better machinery condition and the fact that the first divestment occurs in the fourth or fifth year. The benefit obtained by the divestment is higher than the investment flow in the present value for all groups of tractors, contributing to justifying machinery replacement, confirming the findings of Grano and Abensur (2017).

The variations identified among the analyzed semesters for the tractors in groups A, B, and C and the mean results that favor replacement show that, based on the Monte Carlo simulation, the probability of obtaining a negative NPV, that is, the present value of scenario II being lower than that of scenario I, is very low it is lower than those of all the analyzed models (Table VI).

The percentages of negative values found for the tractors in groups A, B, and C (Table VI) were 7.61, 13.37, and 7.91%, respectively. The accumulation of these values occurred by adjusting the blocks by inserting the limit of "0" (zero), to accumulate all the negative results found in the simulation and separate them from the positive values.

Table VI: Probabilities analyzed by the Monte Carlo simulation for tractors.

Group A			Group B			Group C		
Block (US$)	***Frequency***	***Cumulative (%)***	***Block (US$)***	***Frequency***	***Cumulative (%)***	***Block (US$)***	***Frequency***	***Cumulative (%)***
−53,253	2	0.02%	−54,778	2	0.02%	−42,519	2	0.02%
−38,607	1	0.03%	−38,813	19	0.21%	−27,178	31	0.33%
−23,961	22	0.25%	−22,849	134	1.55%	−11,836	208	2.41%
−9,316	198	2.23%	−6,884	596	7.51%	0,00	550	7.91%
0,00	538	7.61%	0,00	586	13.37%	3,505	282	10.73%
5,330	464	12.25%	9,081	1,091	24.29%	18,846	1875	29.48%
19,976	2434	36.58%	25,045	2,658	50.86%	34,188	2839	57.87%
34,622	3126	67.84%	41,010	2,586	76.72%	49,529	2525	83.12%
49,268	2189	89.72%	56,975	1,623	92.95%	64,870	1228	95.40%
63,913	860	98.32%	72,939	550	98.45%	80,212	383	99.23%
78,559	156	99.88%	88,904	139	99.84%	95,553	71	99.94%
93,205	12	100.00%	104,869	16	100.00%	110,894	6	100.00%
More	0	100.00%	More	0	100.00%	More	0	100.00%

The results are shown in Table VI increase the confidence in asserting that scenario I (replacement of machinery with new machinery) for citrus-spraying activities is economically viable because the possibility of obtaining a negative NPV is very low.

The results indicate that the renewal of the fleet of tractors with tires used in the spraying of citrus groves, used in the present study, must occur in the fourth year of operations, due to the increase in costs, associated with the tax benefit that had great relevance in the results. found, as well as the economic impact on cash flow resulting from investments and the resale of tractors.

5. Conclusions

Fleet renewal is the best economic decision when compared with the alternative of renovation for citrus farm tractors, considering the different financial impacts of investments, costs, and tax benefits in the agricultural company cash flow. Specifically, fleet renewal is feasible in the fourth year of operation.

The mean use of 1,500 hours/machine/semester led to a real increase of 5.3% per semester in the variable costs due to the wear of equipment components.

The Monte Carlo simulation increased the robustness of the DCF results, as it considered the inherent uncertainty in the cost distribution patterns, showing that tractor renewal is the best decision in more than 93% of the investigated possibilities.

In addition to contributing to the scarce amount of empirical information in the literature, the model provides greater security for producers and decision-makers of citrus-producing agricultural companies by implementing a traditional DCF approach adding a Monte Carlo simulation for the cost variables, mitigating the risk in the assessment process.

The present work presents a methodological tool for economic evaluation to verify the viability of reforming or purchasing agricultural tractors with tires, used in the spraying of citrus orchards, thus creating values for managers and decision makers, since the search for better margins and profitability, led to an increase in the use of agricultural machinery, aiming at increasing the efficiency of operations and consequently reducing the cost of production, which is reflected throughout the agribusiness chain.

Extrapolation of these results should take into account the specificities of the study, such as i) the minimum attractive rate of return, ii) the fact that the values of investments and costs reflect the reality of the studied company, iii) the fact that the costs of renovated machinery were estimated by the real rate of cost growth, and iv) the differentiated income tax rate.

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