Computers and Electronics in Agriculture 194 (2022) 106792

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

# CANBUS-enabled activity-based costing for leveraging farm management

Michele Mattetti, Marco Medici, Maurizio Canavari, Massimiliano Varani *

*Department of Agricultural and Food Sciences, Alma Mater Sudiorum, University of Bologna, Bologna, Italy*

ARTICLE INFO

*Keywords:*
Farm management information system
CANBUS
Data-driven farming
Economic effects
Decision analysis

ABSTRACT

The improvement of economic management in farms has become an important research topic in recent decades as the most dominant feature of current farm management information systems (FMIS). Production cost statistics allow farmers to assess the economic impact of farm activities and compare historical data against previous farm practices or competitors' activities. Therefore, the availability of reliable cost data is of utmost importance for FMIS, especially data on agricultural machinery usage. Technical sheets, grey literature, and international standards provide estimates of farm operation costs, but they suffer from low accuracy because agricultural machinery is subjected to the high variability of both environmental and working conditions. Based on these considerations, this work aims to develop a novel methodology for cost calculations of field operations harnessing real-world CANBUS data based on the activity-based costing (ABC) approach. The research was conducted on a 198-kW tractor equipped with a CANBUS logger and several implements on which Bluetooth beacons were installed to automatically recognise agricultural operations. The acquired data were processed to identify the daily jobs performed by observing machine position (e.g., field, farm, or road) and operating condition states (e.g., moving, fieldwork, or idling). The ABC approach was applied in two steps: first, cost driver rates were assessed to define capital and non-capital costs; then, the costs of each agricultural operation performed were defined, correlating the cost drivers with the recorded jobs. The results show that fuel and labour costs combined affect 63%–71% of the total cost per hectare for the tested implements. The cost per hectare was found to be highly variable: the biggest gap between the higher and lower values registered with the same implement was 216.48 € $ha^{-1}$. This methodology could help farmers to make more thoughtful decisions about crop, land, and farm operations management.

## 1. Introduction

Over the last twenty years, farms have become larger and more complex organisations, making good governance and the search for profitability crucial aspects of primary food production management. Farmers have begun to reliably control the management processes of crops, to an extent, which includes recording chronologies of all agronomic activities (Doerge, 1999). Moreover, various farm management strategies and methods have been employed to enhance farm productivity and profit. Financial management includes tasks such as accounting, budgeting, planning, and management control. The latter has grown more important in the last decade; unsurprisingly, it is the most dominant feature of current farm management information systems (FMISs), in which it is primarily presented as tools to support farmers in making billing plans, performing financial analysis and planning, calculating economic results, and budgeting (Munz et al., 2020; Paraforos et al., 2017; Tummers et al., 2019).

The expansion of farms facilitates the adoption of such management tools, which, in theory, allows them to simplify farming performance evaluations while improving farmers' decision-making abilities. However, the expansion also augments the lack of management abilities and skills necessary to make the best decisions. Farmers mostly rely on experience, intuition, and personal memory, but these are not sufficient to face the many challenges and risks that characterise modern agriculture (Yang et al., 2018).

### 1.1. Cost monitoring and activity-based costing

Costs are pivotal elements in managerial decisions, especially for large organizations managing several activities and producing diverse outputs. At the farm level, production cost statistics contribute to improving assessments of farm activities, allowing farmers to evaluate farm operations and benchmark them against best or previous practices in their farm's history as well as against the practices of their competitors. The subdivision of the cost-share is dependent on the type of farm;

* Corresponding author.
*E-mail address:* massimiliano.varani@unibo.it (M. Varani).

https://doi.org/10.1016/j.compag.2022.106792
Received 29 October 2021; Received in revised form 10 February 2022; Accepted 12 February 2022
Available online 18 February 2022

**Nomenclature**

| | |
|---|---|
| $c$ | Driver rate for tractors and implements (€ $h^{-1}$) |
| $c_i$ | Driver rate assigned at the *i*-th cost item (see) (€ $h^{-1}$) |
| $d_J$ | Job travelled distance (km) |
| $d_T$ | Task travelled distance (km) |
| $\dot{f}$ | Fuel consumed by the engine per unit of time (l $h^{-1}$) |
| $f_J$ | Job fuel consumption (l) |
| $f_T$ | Task fuel consumption v |
| $h$ | Annual working hours (h) |
| $n$ | Equipment economic life (years) |
| $n_e$ | Revolution speed of the engine crankshaft (rpm) |
| $r$ | Money interest rate (%) |
| $t_J$ | Job duration (s) |
| $t_T$ | Task duration (s) |
| $A_J$ | Job worked area ($m^2$) |
| $A_T$ | Task worked area ($m^2$) |
| $C_J^A$ | Job total cost per hectare (€ $ha^{-1}$) |
| $C_J^t$ | Job total cost per unit of time (€ $h^{-1}$) |
| $C^A$ | Total cost per hectare considering every job performed (€ $ha^{-1}$) |
| $C^t$ | Total cost per unit of time considering every job performed (€ $h^{-1}$) |
| $C_{i,J}^A$ | Total resource costs per hectare for each job (€ $ha^{-1}$) |
| $C_{i,J}^t$ | Total resource costs per unit of time for each job (€ $h^{-1}$) |
| $C_{i,J,of}^A$ | Cost per hectare of capital and non-capital resources used only in field passes (€ $ha^{-1}$) |
| $I$ | Initial equipment investment (€) |
| $I_i$ | Cost driver in the form of $t_J$ for all resources, except for fuel, which takes the form of $f_J$ (s)/(l) |
| $ID_i$ | Implements identifiers (–) |
| $ID_J$ | Job identifiers (–) |
| $L$ | Location identifiers |
| $M_e$ | Actual engine torque as a percentage of $M_r$ (%) |
| $M_f$ | Sum of the engine frictional and thermodynamic loss, pumping torque loss, and losses of fuel, oil, and cooling pumps as a percentage of $M_r$ (%) |
| $M_r$ | Maximum engine torque available (Nm) |
| $P_e$ | Actual engine power (kW) |
| $P_{e,T}$ | Task average engine power (kW) |
| $Pof_J^A$ | Percentage of the cost per hectare spent on field for each job (%) |
| $S_n$ | Equipment salvage value (€) |
| $T_f$ | Temperature of the fuel (°C) |
| $V$ | Ground speed measured through the GNSS receiver (km $h^{-1}$) |
| $V_T$ | Task average ground speed (km $h^{-1}$) |

for instance, a large share of field crop farm costs is from machinery, which comprises assets associated with depreciation and resource consumption (Hunt and Wilson, 2015; Vozka, 2007; Wang et al., 2021; Weersink et al., 2008). Moreover, the recent introduction of precision farming technologies in machinery could increase field operation efficiency and reduce resource waste. However, the purchase cost of these more advanced machines is higher (Zhang et al., 2018).

Thus, the existence of robust and reliable cost data is of utmost importance for making informed decisions as they allow farm analysts to measure farm efficiency and advise farmers accordingly. As a result, farmers can be more aware of how to improve the efficiency and profitability of their work. Estimations of farm operation costs are available from technical sheets and grey literature but they suffer from rapid changes in prices and technology, thereby losing interest each year. Furthermore, ASAE developed standards to calculate the cost of machines (ASAE, 2015) but they are based on the typical conditions of North American farms, leading to significant margins of error in different contexts, such as small-scale and organic farms, which are more popular in Europe. For example, tractors can operate at very different power levels as a function of their traction elements (i.e., pneumatic tires, tracks, etc.), the soil conditions, and the implement setup (Balsari et al., 2021; Mattetti et al., 2020; 2017). This implies to cope with high variability of machinery usage and fuel consumption, leading to very different cost estimates even on the same farm.

Unfortunately, most farmers rely on rough cost estimations alone, particularly to assess general costs (overhead), which are allocated to final products based on only a few cost drivers (i.e., factors causing a change in the cost of an activity) – sometimes just direct labour or machine hours in tabular formats. In enterprises that typically use shared resources to produce a variety of goods and services, this practice can be inaccurate and misleading because it may overestimate the cost of one final product and underestimate the cost of another, leading to a bias known as ‘cross subsidisation’ (Gupta and Galloway, 2003). This phenomenon can affect the evaluation of crop profitability and lead to inappropriate management choices. The risk of cross-subsidisation can be minimised by adopting a direct costing approach, such as the widely known practice of attributing variable costs to final products (e.g., fuel cost and agronomic input costs to food production for field crop farms or operations carried out for contractors). Activity-based costing (ABC) was introduced by Kaplan and Cooper (1998) and is one of the most well-known budget management tools for direct costing. It can be considered as a different approach to management, not just budgeting, as well as a way to interpret economic performance. While most of the general farm costs (e.g., input costs, insurance costs, equipment purchases, amortizations) in conventional cost allocation approaches are allocated to final products on arbitrary bases, such as variation in input stocks across years, agricultural products, or approximate time of use of machinery, an ABC system requires the collection of general costs for each performed activity (e.g., ploughing, subsoiling), identification of quantitative measure of the activity output (i.e., cost drivers), and calculation of activity utilisation rates. ABC implementation is a complex process since it requires more data than traditional costing approaches, but it provides more informed estimates of product costs and focuses on managing activities to reduce costs.

### 1.2. Agricultural machinery costs

Among cost drivers, machinery costs are one of the most difficult for farmers to monitor; therefore, they are often overlooked. The only reason for farmers to monitor the activities of machinery is that they are tax-deductible expenses. Modern agricultural machinery integrates several sensors into the CANBUS network following the J1939 and ISO 11783 (ISOBUS) standards. These technologies are well established in farms, and machinery embedded with these technologies has been commercially available for years: the first tractor equipped with the CANBUS was released in 1994 (Young, 1994), and the first implement equipped with ISOBUS was released in 2001 (Stone et al., 2008). Both technologies help collect detailed and specific data describing machinery operation (e.g., the torque developed by the engine, engine revolution speed) and represent a useful source of data that must be mined to obtain the information required for farm decision-making. In fact, the use of CANBUS and ISOBUS technologies can pave the way to improving cost allocation to farm output products or activities, creating an opportunity for the application of direct costing approaches. These approaches can also fit particularly well with site-specific operations in the context of precision agriculture, which is characterised by its substantial potential to improve agricultural performance (Backman et al., 2019; Pedersen et al., 2019).

Based on these considerations, this work aims to develop a novel methodology for cost calculations of field operations based on real-world CANBUS data and the ABC approach to achieve more precise monitoring and allocation of farm costs and production costs.

## 2. Materials and methods

The developed method was applied to a 6230 CVT row-crop tractor made by Steyr (CNH Industrial N.V., Amsterdam, NL) with an engine power of 198 kW, an unballasted mass of 7300 kg and equipped with a continuously variable transmission (CVT) (LECTURA SPECS, 2015). This tractor was chosen mainly for its richness of embedded sensors, which allow for comprehensive identification of the operating state. The tractor was used by six different professional operators and employees of a contractor, and the data acquisition system was completely automated; thus, the operators were not responsible for the recording process to avoid any influence on the tractor usage. The tractor was monitored for approximately two years (from October 2018 to January 2021) using a custom-made CANBUS data logger developed in previous studies by one of the authors of this research (Mattetti et al., 2021; Molari et al., 2013). The tractor was used for 177 days, equivalent to 1323 h. The CANBUS data logger was equipped with an embedded GNSS receiver (sampling rate of 5 Hz, circular error probable (CEP) of 2.5 m) and a Bluetooth Low Energy (BLE) scanner compatible with Bluetooth 5.0. The BLE scanner was designed to scan the nearby BLE beacons attached to the implements hitched to the monitored tractor and record their identifiers ($ID_i$). This approach was used because most of the contractor's implements were not ISOBUS compliant.

### 2.1. Data collection

The CANBUS logger was set up in order the signals with the following suspect parameter numbers (SPNs) and parameter group numbers (PGNs) (ISO, 2012; SAE, 2013):

SPN 544 and PGN 65251: '*Engine Reference Torque*' reports the maximum engine torque available, denoted as $M_r$ in the following equation; sampling rate of 0.2 Hz.

SPN 513 and PGN 61444: '*Actual Engine - Percent Torque*' reports the torque as a percentage of $M_r$ and is denoted as $M_e$ in the following equation; sampling rate of 50 Hz.

SPN 513 and PGN 5398: '*Nominal Friction - Percent Torque*' reports the sum of the engine frictional and thermodynamic loss, pumping torque loss, and losses of fuel, oil, and cooling pumps as a percentage of $M_r$, denoted as $M_f$ in the following equation; sampling rate of 20 Hz.

SPN 190 and PGN 61444: '*Engine Speed*' reports the revolution speed of the engine crankshaft, denoted as $n_e$ in the following equation; sampling rate of 10 Hz.

SPN 1883 and PGN 65090: '*Rear PTO Output Shaft Speed*' reports the speed of the rear PTO; sampling rate of 10 Hz.

SPN 1882 and PGN 65090: '*Front PTO Output Shaft Speed*' reports the speed of the front PTO; sampling rate of 10 Hz.

SPN 183 and PGN 65266: '*Engine Fuel Rate*' reports the fuel consumed by the engine per unit of time, denoted as $\dot{f}$ in the following equation; sampling rate of 10 Hz.

SPN 1873 and PGN 65093: '*Rear Hitch Position*' reports the position of the rear three-point hitch; sampling rate of 10 Hz.

SPN 174 and PGN 65262: '*Engine Fuel Temperature 1*' reports the temperature of the fuel, denoted as $T_f$ in the following equation; sampling rate of 1 Hz.

In addition to these signals, the machine's position and ground speed ($V$) were measured through the embedded GNSS receiver. From the recorded data, the actual engine power $P_e$ was calculated using Equation (eq.) 1:

$$P_e = M_r \frac{M_e - M_f}{100} n_e \quad (1)$$

Using MathWorks's MATLAB (Natick, MA, USA), the signals were interpolated at 10 Hz using a cubic spline for a consistent sampling rate of all the signals and to remove any high-frequency disturbances.

### 2.2. Data processing

The signals were classified according to the types of agricultural activities performed for crop production. To this end, the classification scheme proposed by Mattetti et al. (2021) was adopted. According to this approach, the data were classified based on two parameters: 1) the machine position (e.g., field, farm, or road) and 2) the operating condition states (e.g., moving, fieldwork, or idling). The former was determined using a shapefile containing the geographic coordinates of roads, field boundaries, and farm units. An identification variable ($L$) was assigned to each position. The latter was determined according to the specific uses of the tractor subsystems (i.e., transmissions, three-point linkage, PTO). Combining these two classifications, the following work states were defined: on-road moving, off-road moving, field work, idle@field, idle@farm, and unclassified.

In this context, a task was defined as a portion of signals during which neither the work states nor hitched implement varied. Each task was tagged to a certain location and implement through variables $L$ and $ID_i$, respectively. The tasks are further described by the following parameters:

- Duration ($t_T$)
- Average ground speed ($V_T$)
- Average engine power ($P_{e,T}$)
- Fuel consumption ($f_T$), according to eq. (2):

$$f_T = \int_{t_T} \dot{f}\, dt \quad (2)$$

Only for those tasks that took place in a field was the worked area ($A_T$) considered and calculated using GNSS coordinates according to the approach proposed by Heiß et al. (2019). For moving tasks, the tractor's travelled distance ($d_T$) was calculated using eq. (3):

$$d_T = V_T t_T \quad (3)$$

The collected data included several errors leading to task misclassification and other erroneous results. This may have been caused by a temporary signal loss of the GNSS receiver, inadvertent driver manoeuvres, or driver change-of-mind situations (i.e., situations where the driver started a manoeuvre but immediately changed the type of manoeuvre). These situations resulted in very short tasks that could complicate the subsequent data analysis since they could not be classified to any field activity. Thus, to limit possible bias, tasks shorter than 10 s or with $A_T$ lower than 0.3 ha were excluded from the analysis. That task filtering removed tasks accounted of 6.2 h – equal to 0.77% of the duration of the entire dataset and accounting for a fuel consumption of 0.26% of the total fuel consumed in the monitoring campaign – so the impact of this filtering was negligible.

A job was defined as a sequence of tasks leading to a field activity (Bochtis et al., 2019), including implement hitching at the farm, moving the tractor to the field, field work, moving the tractor to the farm, and tractor parking. Under this definition, a job was identified by a sequence of tractor tasks classified in certain work states; this sequence may change in both structure and duration depending on the activity performed. Thus, to classify a job, a specific encoding for automatically identifying sequences of work states was adopted, taking the form of a regular expression that searched for the following patterns:

(1) idle@farm: optional
(2) off-road moving: optional
(3) on-road moving: mandatory
(4) off-road moving: mandatory
(5) (repetitive sequence of field passes, headland turns, idle@field): mandatory
(6) off-road moving: optional
(7) on-road moving: optional
(8) idle@farm: optional

Each matching sequence of tasks was assigned a job identifier ($ID_J$). Fig. 1 reports the trajectory data of the tractor in two subsequent jobs. On the left side, the trajectory data are illustrated by work state classification; on the right, the data are illustrated by job classification. In 'job – 1′, the tractor moves from a farm unit to a field next to the farm, passing states 1, 3, 4, and 5, while in 'job – 2′, the tractor moves from one field to another and then moves back to the farm unit, passing states 2, 3, 4, 5, 6, 7 and 8. The last three states were assigned to 'job – 2′ since it was the last job of the day.

For each job, the following parameters were calculated:

- Duration ($t_J$) as the sum of durations of all the tasks assigned to each $ID_J$:

$$t_J = \sum t_T(ID_J) \tag{4}$$

- Fuel consumed in a job ($f_J$) as the sum of fuel consumed for all the tasks assigned to each $ID_J$:

$$f_J = \sum f_T(ID_J) \tag{5}$$

- Distance travelled by the tractor ($d_J$) as the sum of the distances travelled by the tractor during moving tasks assigned to each $ID_J$:

$$d_J = \sum d_T(ID_J) \tag{6}$$

- Area worked ($A_J$) as the sum of the worked areas of all the tasks taking place on a field assigned to each $ID_J$:

$$A_J = \sum A_T(ID_J) \tag{7}$$

### 2.3. Application of ABC

In applying the ABC framework in the context of this study, the costs that can be assigned to the performed activities (i.e., tasks and jobs) were defined in two steps: first, cost driver rates were assessed, defining capital and non-capital costs, which helped to define job costs as described in Medici et al. (2021).

#### 2.3.1. Cost driver rates

Machines and implements are capital goods commonly shared among several field operations, and they are mostly used in combination. Their capital costs include investment, interest, and depreciation. Reasonably, the annual costs of interest and depreciation can be estimated based on the annuity distributed over the economic life of the machine. A cost driver is a quantitative measure of the use of a resource. In this study, duration drivers, which represent the amount of time consumed by the resource (e.g., machines, implements, and human labour), and intensity drivers, which account for the quantity of fuel used, were directly assigned to each job. Driver rates (€ per unit time or mass) were estimated both for capital goods (i.e., tractors and implements) and non-capital resources (i.e., fuel and labour). The driver rates for tractors and implements were calculated with eq. (8), and the average yearly equipment costs were adapted from Schoney (1980):

$$c = \left[\frac{(I - S_n)r}{1-(1+r)^{-n}} + S_n r\right]\frac{1}{h} \tag{8}$$

where $I$ is the initial equipment investment in € obtained from the purchase bill; $h$ represents the annual working hours of each tractor and implement; $S_n$ is the salvage value after $n$ years in €, equal to 20% of the initial investment; $n$ is the economic life in years; and $r$ is the annual interest rate, assumed to be equal to 3% to account for ownership and operating costs, in line with Kay et al. (2016). Furthermore, an economic life of 10 years for most tillage implements, 8 years for the seeder, and 15 years for the tractor were assumed, in line with the available literature (Edwards, 2015; Medici and Canavari, 2021). The annual working hours ($h$) were estimated considering the estimated life of similar equipment reported by ASAE (2015), resulting in 200 annual working hours for all the implements except for the seeder, which was determined to have 150 annual working hours. For the tractor, an annual value of 611 h was calculated based on the 1323 h recorded over the monitored period of 26 months. Table 1 reports the main specifications of the equipment used most often by the tractor in the recorded period.

The driver rates for non-capital resources (i.e., fuel and labour) were assumed based on the market costs: a value of 0.77 € $l^{-1}$ was adopted for

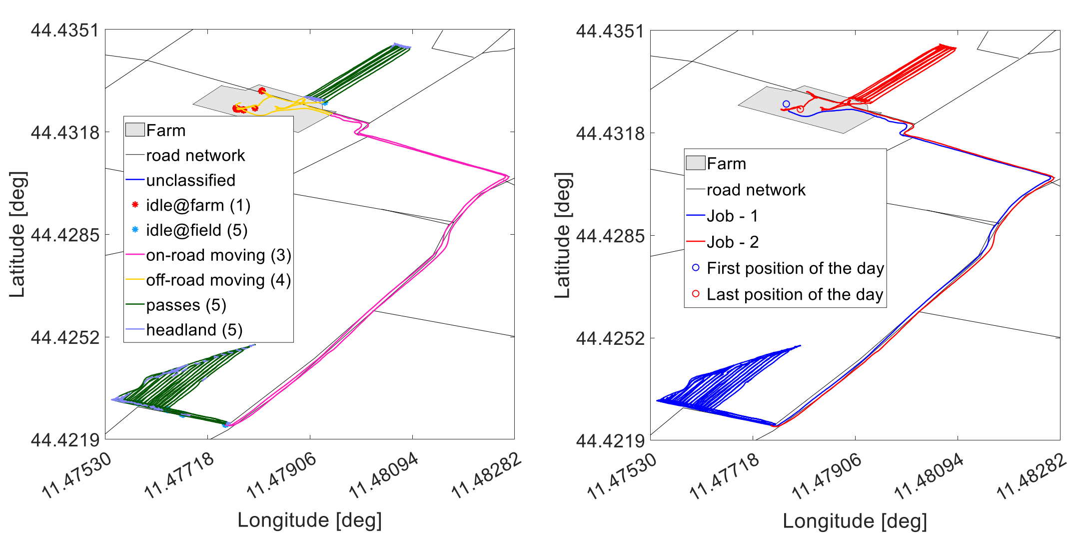


**Fig. 1.** Tractor trajectory data by tractor classification states (left) and job classification (right).

**Table 1**
Main equipment specifications and investment costs.

| Equipment model | Equipment type | Abbreviation | Implement width (m) | Implement mass (kg) | Initial investment ($I$) (€) |
|---|---|---|---|---|---|
| Steyr 6230 CVT (CNH Industrial N.V., Amsterdam, NL) | Tractor | *tra* | (-) | (-) | 111,858.00 |
| MA/AG EDX780C/28 (MA/AG S.r.L., Casalbuttano (CR), IT) | Cultivator | *cul* | 3.9 | 2230 | 8,240.00 |
| ER.MO FSV21024ML (ER.MO S.p.A., Casalbuttano (CR), IT) | Plough | *plo* | 1.8 | 2200 | 8,034.00 |
| Frandent R303.19 (Frandent Group S.R.L., Osasco (TO), IT) | Power harrow | *ph3* | 3.0 | 1547 | 14,183.10 |
| PÖTTINGER Terradisc 3000 (PÖTTINGER Landtechnik GmbH, Grieskirchen, DE) | Seeder | *see* | 3.0 | 1350 | 5,150.00 |
| Power harrow Frandent RP502.28 (Frandent Group S.R.L., Osasco (TO), IT) | Power harrow | *ph5* | 5.0 | 3378 | 27,501.00 |

fuel (agricultural diesel) while an hourly salary of 19.60 € h$^{-1}$ was considered for labour costs, in line with projects funded by the EU Rural Development Programme in the Emilia-Romagna region (Italy). The driver rates are reported in Table 2. The machinery costs were calculated using eq. (8) and the investment costs reported in Table 1. Table 2

### 2.3.2. Job costs

Agricultural machines can be used by farmers or managed by contractors. Thus, job costs were reported per both surface and time units. Costs per hectare can benefit farmers, who are familiar with the production costs per unit of output (e.g., tons) that in turn depend on yields, expressed, e.g., as tons per area. At the same time, hourly costs can be directly interpreted by contractors who are mostly focused on the profitability of their activities and the return of their investment in machinery across time scales. Therefore, to calculate the total cost of each job performed, cost drivers were multiplied by the quantity or duration associated with each resource use. For each job, total resource costs per hectare (i.e., $A_J$) ($C^A_{i,J}$) and time (i.e., $t_J$) ($C^t_{i,J}$) were calculated with eqs. (9) and (10), respectively:

$$C^A_{i,J} = c_i I_i / A_J \tag{9}$$

$$C^t_{i,J} = c_i I_i / t_J \tag{10}$$

where $c_i$ is the driver rate assigned at the $i$-th cost item (Table 2) and $I_i$ is the cost driver that takes the form of the job time ($t_J$) for all resources (eq. (4)), except for fuel, which takes the form of fuel consumed for the job ($f_J$). For each job, the total cost was calculated as the sum of the costs of the capital and non-capital resources used (eqs. (11) and (12)):

$$C^A_J = \sum_i C^A_{i,J} \tag{11}$$

$$C^t_J = \sum_i C^t_{i,J} \tag{12}$$

The percentage of the cost per hectare spent on fields for each job ($Pof^A_J$) was calculated as:

$$Pof^A_J = \frac{\sum_i C^A_{i,J,of}}{C^A_J} * 100 \tag{13}$$

where $C^A_{i,J,of}$ is the cost per hectare of the capital and non-capital resources used only in field passes, headland turns, and idling at fields, excluding all the other activities listed in the patterns described in Section 3.2.

The obtained values of $C^A_J$, $C^t_J$, and $Pof^A_J$ were organised in boxplots (Figs. 6, 7, and 8, respectively) grouped by the implement mounted on the tractor during each job observing the values of $ID_i$.

Moreover, the total costs of every job performed by the tractor were calculated with:

$$C^A = \sum_j \frac{\sum_i C^A_{i,J} A_J}{A_J} \tag{14}$$

$$C^t = \sum_j \frac{\sum_i C^A_{i,J} t_J}{t_J} \tag{15}$$

The obtained values were visualised in a stacked bar plot grouped by implement observing the values of $ID_i$ (Fig. 5).

**Table 2**
Cost driver rates for capital and non-capital resources.

| Cost item | Cost item nomenclature | Driver rate $c$ (€ h$^{-1}$) |
|---|---|---|
| Fuel | *f* | 0.77* |
| Labour | *OP* | 19.60 |
| Machinery | *cul* | 3.56 |
| | *plo* | 3.47 |
| | *ph3* | 6.12 |
| | *see* | 2.37 |
| | *ph5* | 11.88 |
| | *tra* | 13.37 |

*value per unit of mass (€ l$^{-1}$).

## 3. Results and discussion

The work states describing all the tractor activities are shown in Fig. 2. The tractor was idle more than the average reported in other studies (i.e., 20%) (Jenkins, 1960; Molari et al., 2019; Perozzi et al., 2016), which might be due to the longer duration of the data acquisition process that caused longer idling activities for machine servicing. Moreover, the extent of moving tasks was particularly high compared with a previous study conducted in similar conditions (Mattetti et al., 2021), which might be because the monitored tractor was managed by a contractor and was used to cover a larger area, as the farther fields were

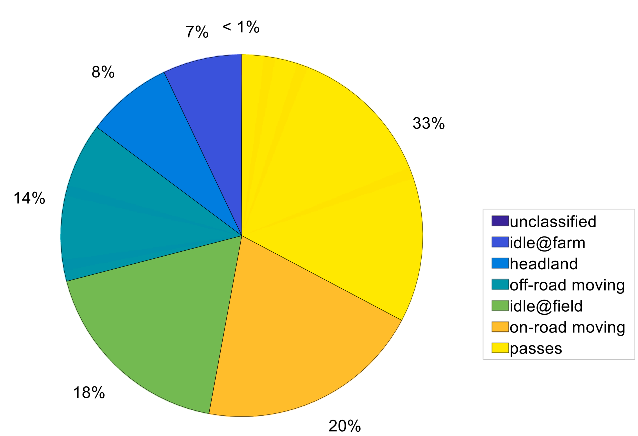


**Fig. 2.** Time contribution of each work state on the entire tractor activity.

55 km away. Last, turning to the work state, the tractor was used for working on fields 59% of the time, which is a typical value for this machine class (Mattetti et al., 2021).

Signal processing identified 25,519 tasks grouped into 197 jobs. Some tasks were not assigned to any job because they did not match the defined job identification pattern; these tasks make up 31% of the entire acquisition duration. In these cases, the tractor was mainly used for moving activities such as moving implements from one farm unit to another. This occurred because the tractor was often used for moving tasks due to its large area of operation.

The durations of the detected jobs ranged from 25 to 782 min with a median value of 156 min. The time contribution of each tractor work state among the jobs is reported on the left of Fig. 3. The largest time contribution is provided by the passes state, with a median value of 67%; the second-largest contribution was from the headlands, which contributed approximately 22%. The fuel consumption contribution of each work state among the jobs is reported on the right side of Fig. 3. The boxplot resembles that on the left of Fig. 3, but the contributions are mostly skewed towards the passes tasks since the fuel consumed is a combination of the fuel rate (i.e., engine load) and the work state duration, as passes tasks are more energy-consuming than the other work states (Cucinotta et al., 2019). The fuel contribution of the passes tasks reaches 88% in fields, where the primary time contribution is from passes states.

Fig. 4 reports the cumulative distribution of the ratio between $A_J$ and $d_J$. The median value of the distribution is 0.25 ha km$^{-1}$, but this value may significantly change across jobs as a function of the relative distances between fields. The values observed in this study are much lower than those reported in other studies where it was assumed that, on average, tractors travel 2 km for each worked hectare (i.e., the ratio between $A_J$ and $d_J$ is 0.5 ha km$^{-1}$) (Lampridi et al., 2020; Nemecek and Kägi, 2007). This means that the actual amount of fuel used for operations per hectare might be greater than typically assumed.

The total cost per hectare $C^A$ for each implement mounted on the tractor is reported in Fig. 5.

$C^A$ changes significantly depending on the type of implement. Implements characterised by low field capacities, such as the plo, ph3, and see, show the highest costs per hectare. It must also be considered that these implements were mostly used for working small and irregular fields, which are conditions that limit the field capacities of machines. For all the implements, the most significant cost drivers were fuel ($C_f^A$) and labour ($C_{OP}^A$), with their sums reaching 63% and 71% of $C^A$, respectively. The tractor ($C_{tra}^A$), which had a higher driver rate than the implements, made the greatest contribution to capital resources (Table 2). These results can allow for a cost comparison between different tillage activities based on the cost per hectare. For example, the cost per hectare of a conventional tillage system can be compared with that of a minimum tillage system. For a conventional tillage system, this case study found the most convenient solution to be composed of the plo, ph5, and see, with a total cost per hectare of 290.19 € ha$^{-1}$. For a minimum tillage solution composed of the cul and see, the total cost per hectare would be 135.02 € ha$^{-1}$, which is 53% lower than that of conventional tillage. Of course, these savings for minimum tillage do not consider costs other than those of the tillage operation (i.e., weed control and fertilization), but this finding is in line with that of Sijtsma et al. (1998) from small plot calculations. This methodology can help farmers in make-or-buy decisions; in the context of this case study, the high value of $C^A$ registered by the ph3 (Fig. 5) would facilitate the outsourcing of harrowing operations. However, hourly costs (eq. (15)) were instead found to be irrelevant since both the tractor and human labour contributions were taken as constant, with the implement and fuel as the only two varying cost drivers, but not independently: the heavier the agricultural operation, the higher the demanded fuel rate for the field operation. Figs. 6 and 7 report the distributions of $C_J^A$ and $C_J^t$ for each implement. The median values of $C_J^A$ grouped by implement type (Fig. 6) confirm the fact already observed in Fig. 5, that implements with low field capacities show the highest costs per hectare. This is particularly noticeable when comparing the results obtained by ph3 and ph5, since they are the same type of implement but with different widths: the median value of $C_J^A$ of the ph3 is 3.4 times higher than that of the ph5, even if the latter is more energy demanding and consumes more fuel. This can be also observed in Fig. 7, where the median value of $C_J^t$ of the ph3 is 20% lower than that of the ph5, mainly due to the higher rate of fuel consumption required by the latter.

The highest variability of the $C_J^A$ was registered by the *ph*3, with a difference between the upper and lower limits of 216.48 € ha$^{-1}$. This is mainly due to its small size, which leads it to be often used in small extension fields with irregular shapes; therefore, the time contribution of work states other than passes was significant (Fig. 3). In fact, *ph*5

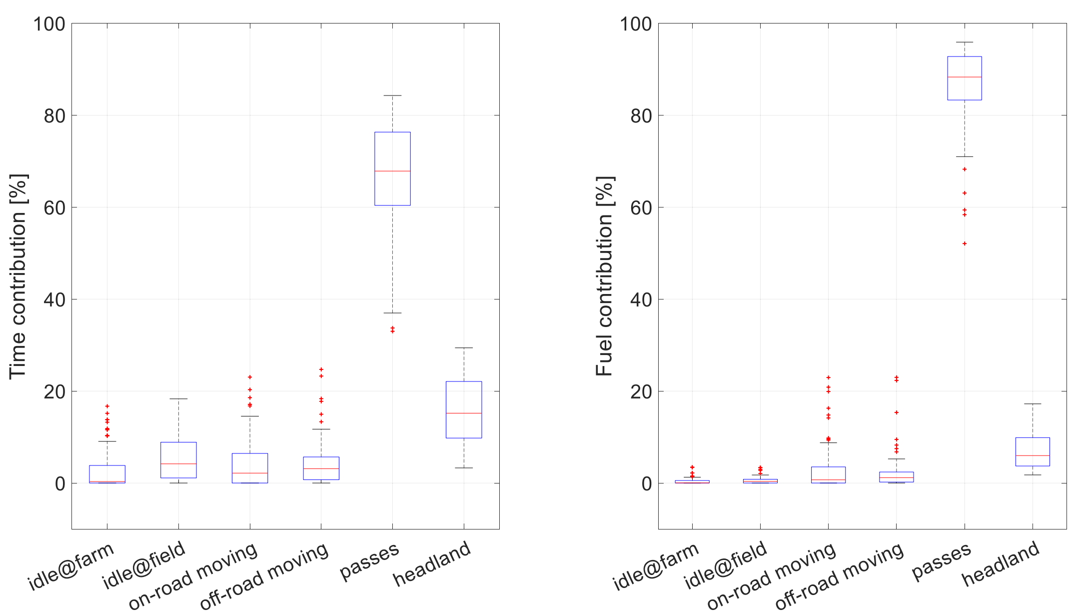


**Fig. 3.** Boxplots reporting the time contributions of the tractor work states among the jobs. Red crosses correspond to the outliers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

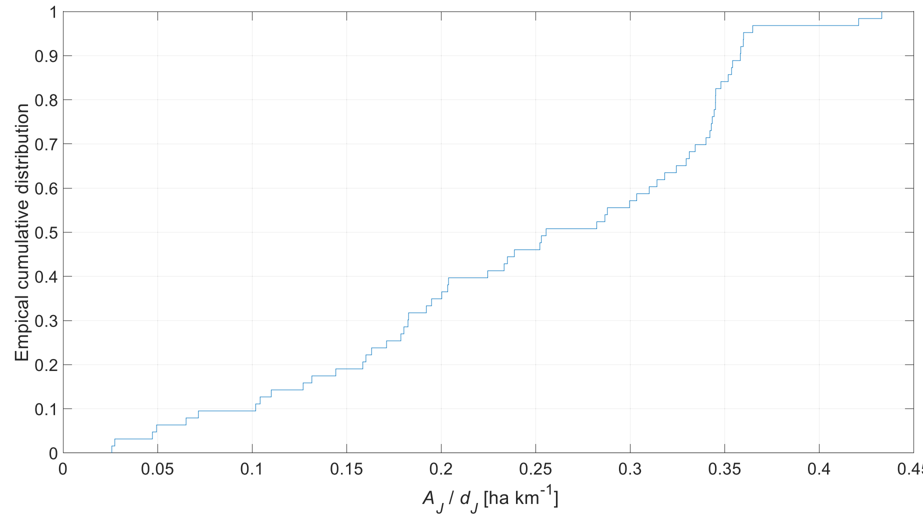


**Fig. 4.** Empirical cumulative distribution of the ratio between the job worked area ($A_J$) and job moving distance ($d_J$).

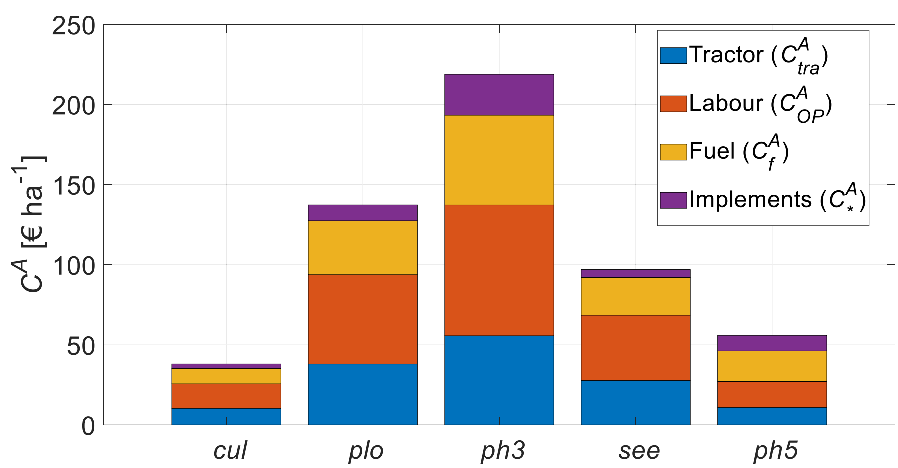


**Fig. 5.** Impact of each cost driver on the total cost per hectare ($C^A_J$) of every tested implement. * value is cul for the cultivator, plo for the plough, ph3 for the 3 m wide power harrow, see for the seeder and ph5 for the 5 m wide power harrow.

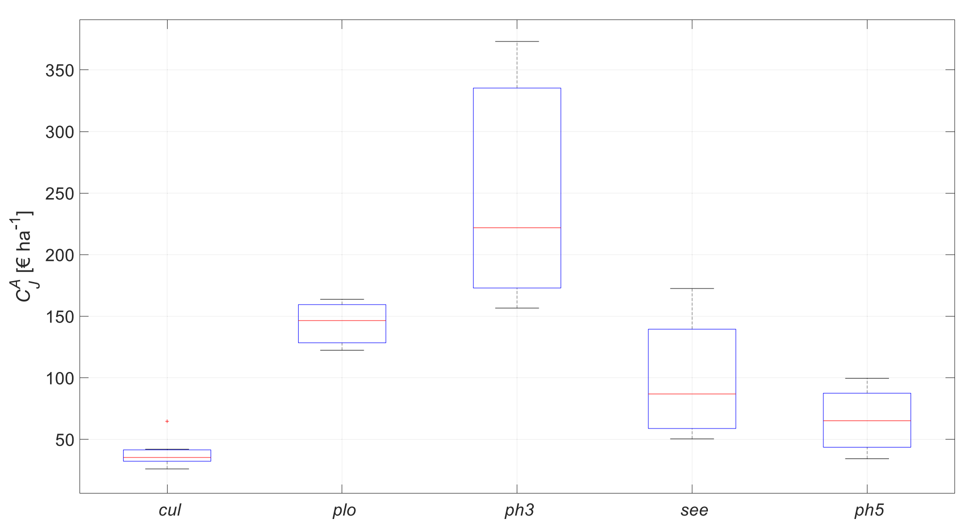


**Fig. 6.** The total cost per hectare ($C^A_J$) grouped by implement mounted on the tractor. cul = cultivator; plo = plough; ph3 = 3 m wide power harrow; see = seeder; and ph5 = 5 m wide power harrow.

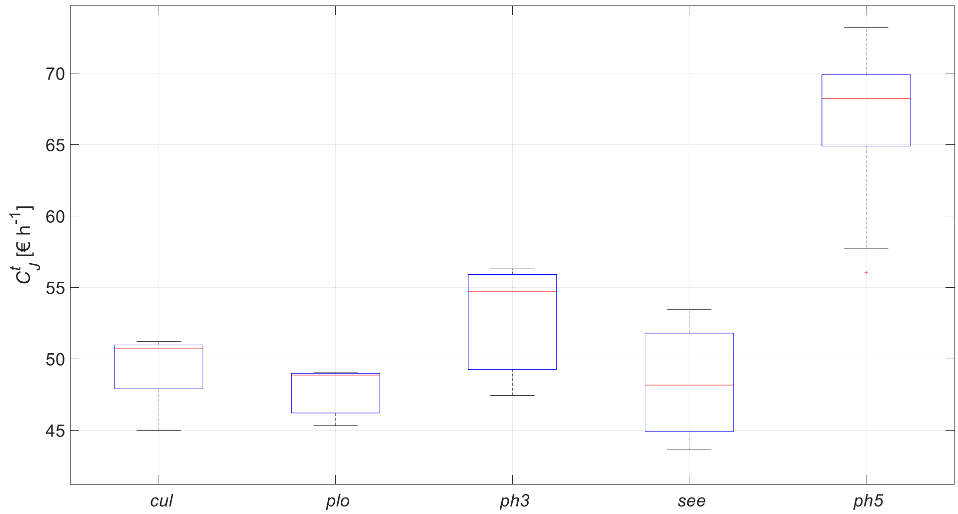


**Fig. 7.** The total hourly cost ($C_J^t$) grouped by implement mounted on the tractor. cul = cultivator; plo = plough; ph3 = 3 m wide power harrow; see = seeder; and ph5 = 5 m wide power harrow. Red crosses represent the outliers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

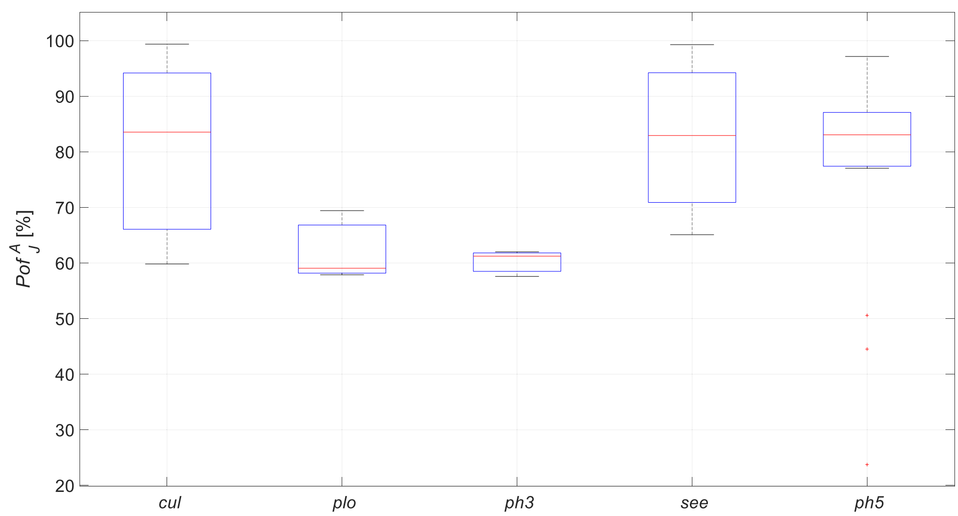


**Fig. 8.** Percentage of the cost per hectare of field. cul = cultivator; plo = plough; ph3 = 3 m wide power harrow; see = seeder; and ph5 = 5 m wide power harrow. Red crosses represent the outliers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

registered a variability 3.1 times lower than *ph*3 because it is mainly used on large and regular-shaped fields where the $A_J/d_J$ ratio is high. On the other hand, the variability of $C_J^t$ registered by the *ph*5 is 1.74 times higher than that of the *ph*3: the variability of $C_J^t$ for the *ph*5 is mainly affected by the fuel rate consumption variability, which is directly proportional to the energy required to operate it. Operational parameters such as tractor speed, soil typology, and moisture content are the main cause of this variability.

The analysis of the percentage of the cost per hectare of field ($Pof_j^A$) presented in Fig. 8 shows that for all the considered implements, the median value of the percentage of $C_j^A$ due to the actual work on the field ranged from 60% to 91%. The high variability showed by some implements, such as *cul* and *see*, was mainly due to variability in the distance of the field tilled by the contractor from the farm.

## 4. Conclusions

Machines embedded with CANBUS technologies that can collect data automatically are currently available to most farms. In this study, we developed an automated data collection process to feed an ABC system for farming activities. The method was applied using CANBUS data from a large database that covered recurring operating conditions and accounted for a large variety of environmental and human labour factors. Data analysis highlighted that the tractor was used for on-field activities 59% of the time, while the percentage of idling time was 25%. Higher costs per hectare were registered for the implements characterized by lower field capacities. Moreover, fuel and labour were found to be the most significant cost drivers: their sum contributes between 63% and 71% of the total cost per hectare of the tested implements.

The advantage of the methodology reported in this paper is that it will enable farmers to keep track of the working periods of their machines, which are usually accounted for using tables that only consider the average conditions. Moreover, such a system will facilitate accurate recordings of the direct energy used in farms, thereby allowing for evaluation of the energy efficiency in alternative agricultural production systems (e.g., conventional tillage, minimum tillage, no-tillage). The method reported in the study could be further improved by monitoring the entire fleet of machines used by contractors/farms so the annual working hours of implements can be accurately calculated. This will also allow farmers to make informed decisions regarding their investments in machinery and operations management innovations.

*CRediT authorship contribution statement*

**Michele Mattetti:** Conceptualization, Methodology, Software, Investigation, Data curation, Writing – original draft, Writing – review & editing, Funding acquisition, Project administration. **Marco Medici:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Maurizio Canavari:** Writing – review & editing. **Massimiliano Varani:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

This project was supported by MUR (Ministry of University and Research) under the call PRIN (Research projects of significant national interest) notification 2017 “Green SEED: Design of more-electric tractors for a more sustainable agriculture”, grant number: 2017SW5MRC.

## References

ASAE, 2015. ASAE D497.7 - Agricultural Machinery Management Data.
Backman, J., Linkolehto, R., Koistinen, M., Nikander, J., Ronkainen, A., Kaivosoja, J., Suomi, P., Pesonen, L., 2019. Cropinfra research data collection platform for ISO 11783 compatible and retrofit farm equipment. Comput. Electron. Agric. 166, 105008. https://doi.org/10.1016/j.compag.2019.105008.
Balsari, P., Biglia, A., Comba, L., Sacco, D., Eloi Alcatrão, L., Varani, M., Mattetti, M., Barge, P., Tortia, C., Manzone, M., Gay, P., Ricauda Aimonino, D., 2021. Performance analysis of a tractor - power harrow system under different working conditions. Biosyst. Eng. 202, 28–41. https://doi.org/10.1016/j.biosystemseng.2020.11.009.
Bochtis, D., Sørensen, C.A.G., Kateris, D., 2019. Operations Management in Agriculture. In: Operations Management in Agriculture. Elsevier, pp. 159–178. https://doi.org/10.1016/B978-0-12-809786-1.00006-0.
Cucinotta, F., Scappaticci, L., Sfravara, F., Morelli, F., Mariani, F., Varani, M., Mattetti, M., 2019. On the morphology of the abrasive wear on ploughshares by means of 3D scanning. Biosyst. Eng. 179, 117–125. https://doi.org/10.1016/j.biosystemseng.2019.01.006.
Doerge, T.A., 1999. Yield map interpretation. J. Product. Agric. 12 (1), 54–61. https://doi.org/10.2134/jpa1999.0054.
Edwards, W., 2015. Machinery management: estimating farm machinery costs. Ag Decision Maker A3–A29.
Gupta, M., Galloway, K., 2003. Activity-based costing/management and its implications for operations management. Technovation 23 (2), 131–138. https://doi.org/10.1016/S0166-4972(01)00093-1.
Heiß, A., Paraforos, D. s., Griepentrog, H. w., 2019. Determination of a field boundary using ISO 11783 and D-GNSS data acquired during a ploughing operation, in: Precision Agriculture ?19. Wageningen Academic Publishers, pp. 775–782. 10.3920/978-90-8686-888-9_96.
Hunt, D., Wilson, D., 2015. Farm Power and Machinery Management: Eleventh Edition. Waveland Press.
ISO, 2012. ISO 11783-7:2012 - Tractors and machinery for agriculture and forestry - Serial control and communications data network - Part7: Implement messages application layer — Implement messages application layer.
Jenkins, A.J., 1960. Power and life investigation of the farm tractor drive components. SAE Technical Paper 600322, 1–17.
Kaplan, R.S., Cooper, R., 1998. Cost & Effect: Using Integrated Cost Systems to Drive Profitability and Performance. Harvard Business Press.
Kay, R., Edwards, W., Duffy, P., 2016. Farm Management. McGraw-Hill.
Lampridi, M., Kateris, D., Sørensen, C.G., Bochtis, D., 2020. Energy Footprint of Mechanized Agricultural Operations. Energies 13, 769. https://doi.org/10.3390/en13030769.
LECTURA SPECS, 2015. Steyr 6230 CVT ET Profi Specifications & Technical Data [WWW Document]. URL https://www.lectura-specs.com/en/model/municipal-technology/vehicles-compact-utility-tractors-steyr/6230-cvt-et-profi-1164133?_ga=2.103659269.429034380.1641310706-1596806250.1640004545 (accessed 1.5.22).
Mattetti, M., Maraldi, M., Lenzini, N., Fiorati, S., Sereni, E., Molari, G., 2021. Outlining the mission profile of agricultural tractors through CAN-BUS data analytics. Comput. Electron. Agric. 184, 106078. https://doi.org/10.1016/j.compag.2021.106078.
Mattetti, M., Varani, M., Maraldi, M., Paolini, F., Fiorati, S., Molari, G., 2020. Tractive performance of trelleborg pneuTrac tyres. J. Agric. Eng. 51, 100–106. https://doi.org/10.4081/jae.2020.1031.
Mattetti, M., Varani, M., Molari, G., Morelli, F., 2017. Influence of the speed on soil-pressure over a plough. Biosyst. Eng. 156, 136–147. https://doi.org/10.1016/j.biosystemseng.2017.01.009.
Medici, M., Canavari, M., 2021. Addressing Risk Associated to ICT-Based Technology: Estimation of Financial Parameters. pp. 174–184. 10.4018/978-1-7998-4849-3.ch010.
Medici, M., Mattetti, M., Canavari, M., 2021. A conceptual framework for telemetry data use in agriculture, in: Precision Agriculture ?21. Wageningen Academic Publishers, pp. 935–940. 10.3920/978-90-8686-916-9_112.
Molari, G., Mattetti, M., Lenzini, N., Fiorati, S., 2019. An updated methodology to analyse the idling of agricultural tractors. Biosyst. Eng. 187, 160–170. https://doi.org/10.1016/j.biosystemseng.2019.09.001.
Molari, G., Mattetti, M., Perozzi, D., Sereni, E., 2013. Monitoring of the tractor working parameters from the CAN-Bus, in: AIIA 13. Presented at the Horizons in agricultural, forestry and biosystems engineering, Viterbo.
Munz, J., Gindele, N., Doluschitz, R., 2020. Exploring the characteristics and utilisation of Farm Management Information Systems (FMIS) in Germany. Comput. Electron. Agric. 170, 105246. https://doi.org/10.1016/j.compag.2020.105246.
Nemecek, T., Kägi, T., 2007. Life Cycle Inventories of Agricultural Production Systems.
Paraforos, D.S., Vassiliadis, V., Kortenbruck, D., Stamkopoulos, K., Ziogas, V., Sapounas, A.A., Griepentrog, H.W., 2017. Multi-level automation of farm management information systems. Comput. Electron. Agric. 142, 504–514. https://doi.org/10.1016/j.compag.2017.11.022.
Pedersen, S. m., Medici, M., Anken, T., Tohidloo, G., Pedersen, M. f., Carli, G., Canavari, M., Tsiropoulos, Z., Fountas, S., 2019. Financial and environmental performance of integrated precision farming systems, in: Precision Agriculture ?19. Wageningen Academic Publishers, pp. 833–839. 10.3920/978-90-8686-888-9_103.
Perozzi, D., Mattetti, M., Molari, G., Sereni, E., 2016. Methodology to analyse farm tractor idling time. Biosyst. Eng. 148, 81–89. https://doi.org/10.1016/j.biosystemseng.2016.05.007.
SAE, 2013. Vehicle Application Layer (No. j1939-71).
Schoney, R.A., 1980. Determining capital recovery charges for tractors and combines in times of inflation. J ASFMRA 44, 23–27.
Sijtsma, C.H., Campbell, A.J., McLaughlin, N.B., Carter, M.R., 1998. Comparative tillage costs for crop rotations utilizing minimum tillage on a farm scale. Soil Tillage Res. 49 (3), 223–231. https://doi.org/10.1016/S0167-1987(98)00175-5.
Stone, M.L., Benneweis, R.K., Van Bergeijk, J., 2008. Evolution of electronics for mobile agricultural equipment. Trans. ASABE 51, 385–390.
Tummers, J., Kassahun, A., Tekinerdogan, B., 2019. Obstacles and features of Farm Management Information Systems: A systematic literature review. Comput. Electron. Agric. 157, 189–204. https://doi.org/10.1016/j.compag.2018.12.044.
Vozka, P., 2007. Comparison of alternative tillage systems (PhD Thesis). Cranfield University (UK).
Wang, C., Li, Z., Wang, T., Xu, X., Zhang, X., Li, D., 2021. Intelligent fish farm—the future of aquaculture. Aquacult Int 29 (6), 2681–2711. https://doi.org/10.1007/s10499-021-00773-8.
Weersink, A., Walker, M., Swanton, C., Shaw, J., 2008. Economic Comparison of Alternative Tillage Systems under Risk. Can. J. Agric. Econ./Revue canadienne d'agroeconomie 40, 199–217. https://doi.org/10.1111/j.1744-7976.1992.tb03690.x.
Yang, F., Wang, K., Han, Y., Qiao, Z., 2018. A cloud-based digital farm management system for vegetable production process management and quality traceability. Sustainability 10, 4007. https://doi.org/10.3390/su10114007.
Young, S., 1994. Electronic Control System for GENESIS$^{TM}$ 70 Series Tractors. International Off-Highway & Powerplant Congress & Exposition, Milwaukee (USA). 10.4271/941789.
Zhang, Q., Dvorak, J., Oksanen, 2018. Intelligent machinery for precision agriculture, in: Precision Agriculture for Sustainability. Burleigh Dodds Science Publishing.