Bridging the gap between reliable data collection and the environmental impact for mechanised field operations

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Abstract

Mechanisation is related to an important proportion of the environmental impacts associated with agriculture, mainly due to engine fuel consumption and exhaust gas emissions, and materials production, use and disposal. Despite standardised and extensively accepted methods for environmental impact assessment have been developed, their application to mechanical field operations is still limited. In absence of reliable data, the reductions in environmental impact that are achievable cannot be easily evaluated by studying machinery already available on the market and more suitable machinery or by selecting the proper coupling between the implement and the tractor. This study carries out a comparative Life Cycle Assessment (LCA) of a rotary harrowing operation using different data sources. Data was gathered from: (i) Ecoinvent database, (ii) ENVIAM, a tool developed to support the completion of inventories for agricultural machinery varying the local pedo-climatic, operating and mechanical features, and (iii) primary data directly collected during experimental tests with CAN-bus, GPS and exhaust gases analyser. The analysis showed that using database average data, the resulting environmental load is not always reliable and, in this particular study, it consistently overestimated most outcomes. Moreover, by processing primary data collected using modern technology, the operation could be split in different working phases (effective work, turns, stationary-idling). Thus, specific mechanical features were quantified and this permitted the environmental impact to be evaluated with more detail.

Keywords

Harrowing, CAN-bus, gas analyser, primary data, inventory filling, Life Cycle Assessment

Nomenclature

Variables/nomenclature	**Symbol/abbreviation**	**Unit**
Engine load		%
Engine speed	s	routes s^{-1}
Torque	M	N m
Tractor engine power		kW
Fuel consumption	FC	l h^{-1} kg ha^{-1}
Emission of carbon dioxide	EM CO_2	g [CO_2] h^{-1} kg ha^{-1}
Emission of carbon monoxide	EM CO	g [CO] h^{-1} g ha^{-1}
Emission of nitrous oxides	EM NO_X	g [NO_X] h^{-1} g ha^{-1}
Brake specific fuel consumption	bsfc	g kW h^{-1}
Specific emission of exhaust gases	EMspec	g kW h^{-1}
Climate Change	CC	kg [CO_2 eq]
Ozone Depletion	OD	mg [CFC-11 eq]
Terrestrial Acidification	TA	kg [SO2 eq]
Freshwater Eutrophication	FE	g [P eq]
Marine Eutrophication	ME	g [N eq]
Photochemical Oxidant Formation	POF	kg [NMVOC]
Particulate Matter Formation	PM	kg [PM10 eq]
Metal Depletion	MD	kg [Fe eq]
Fossil Depletion	FD	kg [oil eq]
Controller Area Network	CAN-bus	
ENVironmental Inventory of Agricultural Machinery operations	ENVIAM	
Exhaust Gas Recirculation	EGR	
Functional Unit	FU	
Global Positioning System	GPS	
Life Cycle Assessment	LCA	
Life Cycle Inventory	LCI	
Life Cycle Impact Assessment	LCIA	
Oxygen	O_2	

1 Introduction

During recent decades, there has been a marked growth of interest in quantifying and reducing the environmental impact of agricultural production. It is widely known that agriculture plays a role in concerns over air, soil and water quality (Bacenetti et al., 2016; IPCC, 2006; Schmidt Rivera et al., 2017) and, in particular, mechanisation has been related to a substantial share of these negative effects (Niero et al., 2015). The mechanical operations carried out during farming activities have been held responsible for freshwater pollution and greenhouse gas emissions (Notarnicola et al., 2015). Emissions are affected both by fuel consumption and exhaust gases directly emitted into the air, as well as by the consumption of mineral and fossil resources for materials realisation (i.e. the processes of mineral extraction, energy use and production for the materials that compose the tractor and implement) (Boone et al., 2016; Lee et al., 2016; Mantoam et al., 2016). It must be pointed out that not every agricultural field operation is adequate in a particular working context; the variability of working conditions (local pedo-climatic, mechanical and operative variables) and the availability of machinery options (Barthelemy et al., 1992) affects both assessments of mechanical suitability as well as of environmental impact.

Although recently standardised and widely accepted methods for environmental impact assessment have been developed (ISO 14040 series, 2006), their application to mechanical field operations is still somewhat limited (Lovarelli et al., 2017). This is due to the difficulties in inventory data collection, since they are site and time dependent, and to the difficulty in getting manufacturing data. With regard to inventory data collection, data can be obtained from both a primary source (i.e. directly collected or measured) and a secondary source (i.e. databases, scientific literature). Certainly, primary data are the most reliable but they are also the most difficult and time consuming to get. For agricultural production, specific geographical, temporal and managerial data are highly relevant (Perozzi et al., 2016) and strongly influence the subsequent quantification of environmental impacts. This is mainly because agricultural systems are based on natural variables (e.g., climate and seasonality, temperature and rainfall), on local field-specific variables (soil texture, field shape, etc.) and on the choices made by farmers regarding the machinery adopted and the farm management regimes used, all of which can affect most environmental loads (Bacenetti et al., 2015; Mantoam et al., 2016).

Reliable data are needed. Although secondary data have the advantage of being more easily available, the pitfall is that they may include simplifications and average values that may not be able to accurately describe the studied system. Specifically, the most important side effects of secondary data are that they can make it impossible to quantify the reduction in environmental loads that are achievable with new machines and innovative technology, since machines may already be available on the market (e.g., minimum and strip tillage, sod-seeding) but not included in databases or, improvements could be made by selecting more suitable machines or performing a proper coupling between the implement and tractor. In fact, in the most used database applied in life cycle assessment (LCA) studies (i.e. Ecoinvent) (Weidema et al., 2013), the impact of the most common field operations is included, but is assessed by considering the average pedo-climatic (e.g., soil texture and moisture), operating conditions (field shape, slope and transfer distance) and mechanical conditions (engine features during transfers, turns and working phases); consequently, the results are not always reliable.

Thanks to the availability on the market of modern tractors and implements, and of new techniques or management strategies, the collection of reliable data is more easily facilitated. In particular, with the modern technologies installed on modern tractors such as CAN-bus (controller area network), a huge amount of contemporaneous information is accessible and constantly measurable during field work (Fellmeth, 2003; Lindgren, 2005; Pitla et al., 2016). These data can describe how the engine works as well as instant working features and interactions within the tractor. This makes it possible to increase the reliability of data for modern machinery and to optimise and better manage the use of agricultural inputs (Bietresato et al., 2015).

The aims of this study were:

- to describe the field experiment of a rotary harrowing operation carried out with typical electronic instrumentation available for modern machinery and use the main results of a prediction model for fuel consumption and engine exhaust gases emissions;
- to use the collected data as information to complete an inventory of agricultural machinery suitable for completing environmental analyses;
- to compare the environmental impact quantified with the collected data with one gathered using other data sources in order to understand how the reliability of inventories affects the results of environmental impact assessments of agricultural machinery operations that are quantified by means of the LCA method.

To this purpose, the environmental impact of rotary harrowing operation was evaluated using the LCA approach considering data from different sources.

The achieved outcomes can be useful for:

- LCA practitioners involved in the evaluation of agricultural systems;

- manufacturers and operators of the agricultural machinery sector (implements and tractors) to understand how the environmental performance of their machines can be evaluated without using generic data;
- for policymakers to get information about the sustainability of different field operations and to develop modular subsidies.

2 Materials and methods

To perform a reliable environmental impact assessment of agricultural field operations, the methodological framework proposed in this study (Fig. 1) links:

- ENVIAM (ENVironmental Inventory of Agricultural Machinery operations), a tool developed to support the environmental impact evaluation by fulfilling inventories for field machinery operations (Lovarelli et al., 2016, 2017).
- the recent technologies installed on modern tractors i.e. CAN-bus and related data logger, GPS (Global Positioning System) and engine exhaust gases analyser that permit the mapping of the operation with instantaneous data on tractor's variables, its spatial position and the exhaust gases emitted to air;
- the LCA approach to evaluate how the use of inventory data from different sources affects the environmental results for field operations.

Figure 1 around here

2.1 ENVIAM

The ENVIAM tool was developed to support the environmental impact evaluation due to machinery use in the different work conditions. ENVIAM is specifically focused on the fulfilment of inventories for field machinery operations in defined local working conditions; it includes a database for tractors and one for implements and calculates fuel and lubricant consumption, engine emitted exhaust gases (CO_2, CO, NO_X) and materials depleted along the studied operation (Fig. 2).

Figure 2 around here

The strength of the tool is that the inventory is completed using accurate quantification of mechanical parameters (e.g., tractor and machinery characteristics and coupling), of fuel, lubricant and materials consumption, and of engine exhaust gases emissions. It allows the inventory to follow a more detailed method: the operation is split in several working times and variables such as absorbed power, fuel consumption and related exhausts emissions are calculated in each of these single working times. The identified working times were selected from Reboul (1964) and are most significantly distinguished in the effective work on field, turns at the headlands, transfers, refilling/emptying, maintenance, etc. The mechanical and operative variables (e.g., engine load, engine speed, brake specific fuel consumption, working time) affecting power, fuel and engine exhaust gases are selected for each of the working times and are used to calculate the related fuel consumption and exhaust gases emission; finally, they are summed to obtain the total value of the whole operation. Further details can be found in Lovarelli et al. (2016, 2017).

The substantial differences in the environmental impacts of analyses carried out with local data instead of average data have already been shown through case studies. A further improvement of the tool's quantification capabilities has resulted necessary for more accurate assessments related to machinery innovations. Accordingly, a first concern is that the calculation methods and models in ENVIAM require a quite small amount of input information and therefore, although giving very interesting results, they may represent a simplification of the complex engine-tractor-implement system. Among these, fuel consumption and engine emissions are the major variables that could be improved in view of LCA studies on local contexts. As mentioned above, for both variables, the use of recent devices installed (or installable) in modern tractors and implements can be useful for reliable data collection.

2.2 CAN-bus, GPS and engine exhaust gases analyser

Among the devices developed to map, understand and study the activity of the tractor engine and of the related devices while working on field, the most widespread system is CAN-bus. A CAN-bus is a serial high-speed wired data network connection that is frequently available on modern tractors. It permits electronic devices to communicate with each other and, coupled with storing instrumentation, it permits huge amounts of data directly deriving from the tractor to be collected while working in the field and with a very detailed time scale (Speckmann and Jahns, 1999). CAN-bus was introduced by Robert Bosch GmbH in 1986, initially for automotive applications, but is widely applied to agricultural tractors. It is standardised with SAE J1939 that defines the connections of electronic devices installed on machinery and then also follows a standard protocol ISO 11898 (ISO, 2003).

CAN-bus has resulted in substantial improvements in the monitoring and collection of data. In particular. It can be used for several purposes, such as precision agriculture, on-board diagnostics, and maintenance scheduling, but it can be used also to support sustainability evaluations.

Linked to precision agriculture processes, GPS also plays an essential role: it permits the identification of the geographical position of the tractor and of its related measured variables, in this case measured by means of CAN-bus and/or exhaust gases emission analyser.

Among other instrumentation that is helpful for data collection in terms of sustainability goals, the exhaust gases emission analyser is fundamental. This instrument is normally portable, therefore not usually present on board the tractor; it permits the flow of exhaust gases (e.g., CO_2, CO, NO_X) and O_2 and the temperature of the instrument and of the exhaust gas to be measured with a detailed temporal scale.

Mostly, the use of these collected "big data" is very helpful in terms of sustainability evaluations because it permits each operation to improve the efficiency and control (and potentially reduce) inputs and emissions. The application of the CAN-bus, GPS and exhaust gas analyser has two main advantages: firstly, the continuous monitoring of the operation on field and secondly, the possible development of a robust model because the data are collected in a very detailed temporal scale and split on the different working conditions. Furthermore, such a model can be used to predict the behaviour of the tractor working with other implements and during other operations. This means that the behaviour of the monitored tractor can be reconstructed, even without additional primary data. Moreover, the implementation of tractor engine features (e.g., engine speed, engine torque, absorbed power) as well as of the working time and speed, of the field shape and of the pedo-climatic features (e.g., soil texture), permits a detailed map to be built up of field operations and, when applied to ENVIAM, to calculate its outputs with additional precision.

2.3 Life cycle assessment

LCA (ISO 14040, 2006) is a standardised method adopted worldwide for quantifying the potential environmental impacts of processes for products or services during their whole life cycle using a holistic approach. In more detail, there are four steps in a LCA:

- defining the goal of the study, selection of the functional unit, description of the system and of the system boundary;

- Life Cycle Inventory (LCI) data collection, in which the flow of materials and energy from the studied systems and the environment are identified and quantified;
- Life Cycle Impact Assessment (LCIA), during which, thanks to specific characterisation factors, the inventory data are converted in few numeric indicators of environmental impact;
- interpretation of the results and identification of the process hotspots.

In Section 4, these phases are explained for the environmental impact assessment of the rotary harrowing.

3 Experimental field tests

3.1 Description of field tests

In order to have primary data for the improvement of reliability and applicability of inventories about agricultural machinery, field experiments were carried out in cooperation with the Swedish Machinery Testing Institute (Umeå, Sweden) and the Department of Energy and Technology at the Swedish University of Agricultural Sciences, Uppsala, Sweden. The field experiment was performed in a sandy-loam soil in Umeå, Sweden, with a Valtra N101 tractor (82 kW, Emissive Stage according EU Directive 97/68/EC and following (European Commission, 1997-2016) Stage 3A, equipped with a EGR - Exhaust Gas Recirculation – for NO_X abatement) coupled with a rotary harrow (width 3 m, depth 100 mm) over a total area of 2.08 ha for 2.96 working hours.

The field test was monitored using: (i) CAN-bus for registering engine data and tractor-related data and Dewesoft® (DEWEsoft, Trbovlje, Slovenia) software for data collection and storage; (ii) GPS to have the tractor position and to link this position to the collected data; (iii) Testo® (Testo Inc, Sparta, USA) portable emission analyser for the measurement and storage of the flow of exhaust gases (CO_2, CO, NOx) and related instrument variables. Figure 3 shows the tractor and the on-board mounted gas analyser system.

Figure 3 – Around here

3.2 Data processing

Data processing involved a first geographical and spatial analysis of the field and then the measured variables analysis and model use for fuel consumption and exhaust gases emissions.

The worked field was analysed for its shape: GPS coordinates were used to identify the tractor spatial position and to distinguish the field shape and the working states that describe the tractor working activity. This distinction provided data and results related to at least three working states, as also shown in Fig. 4:

- effective work on field (i.e. moving forward while working, with a straight direction);
- turns at the headlands (i.e. turning position, which was recognised by identifying the angle that defines the direction of the tractor);
- stationary (i.e. no change in position, mainly under idling conditions).

In each state, characterised by similar but not equal working features, the measured fuel consumption and exhaust gases were identified to have a series of values referred to the same grouping of states. The experimental plan was defined foreseeing the split of the field in areas in which variables such as working speed and engine speed differed, which also involves that torque and engine load change.

Figure 4 – Around here

By offsetting the collected data on a temporal basis, both CAN-bus and engine exhaust gases emissions were related to the spatial position of the GPS and, therefore, were linked to each working state. This allowed for:

(i) calculating an average value for each working state (i.e. row, turn and stationary position), and in particular for each row, each turn and each stationary state;

(ii) calculating the regression that characterised fuel and emissions related to each state.

After this step, the modelling was performed. In particular, the modelled variables were:

- fuel consumption (FC; $l\ h^{-1}$) and
- exhaust gases emissions (EM; $g\ [CO_2]\ h^{-1}$, $g\ [CO]\ h^{-1}$, $g\ [NO_X]\ h^{-1}$).

For all of the parameters, modelling was carried out introducing the equation reported below that depends on engine torque (M; Nm), engine speed (s; rpm) and engine-specific coefficients (Jahns et al., 1990; Lindgren, 2005). Torque and engine speed were gathered from the measurements, while the 9 coefficients adopted were calculated referred to the equation modelling the semi-static condition and were identified using the least squares fit. FC and EM were quantified per second, following the sensibility of CAN-bus and gas analyser, and afterwards were quantified for all working states and total working time. The equation was validated through data obtained during measurements completed with the same tractor.

$$FC = c_1 \cdot s + c_2 \cdot s^2 + c_3 \cdot s^3 + M \cdot (c_4 \cdot s + c_5 \cdot s^2 + c_6 \cdot s^3) + M^2 \cdot (c_7 \cdot s + c_8 \cdot s^2 + c_9 \cdot s^3)$$

where:

- FC is fuel consumption (l h^{-1});
- c_1..c_9 are engine-specific coefficients (dimensionless);
- s is engine speed (routes s^{-1});
- M is torque (N m).

FC and EM were also expressed as specific values (brake specific fuel consumption, bsfc, g kW h^{-1}; specific emissions, EMspec, g kW h^{-1}) by taking into account the related absorbed power, in order to be widely comparable.

Data processing on engine exhaust gases is more complex because each gas responds to different conditions, gases presence, temperatures, oxygen concentration, technologies and after-treatment systems and driving abilities (Larsson and Hansson, 2011; Lindgren and Hansson, 2002, 2004). However, by quantifying properly the 9 coefficients, the equation also responds well to engine exhaust emissions (Lindgren, 2005).

3.3 Results of the field tests

Table 1 reports the values of fuel consumption, exhaust gases emissions, absorbed engine power and engine load averaged per row, turn and stationary position characterising the rotary harrowing.

Table 1 around here

In Table 2 the nine engine-specific coefficients adopted during the modelling of fuel consumption and engine exhaust gases emissions are reported.

Table 2 around here

In Fig. 5 the behaviour of the model split in the working states of effective work, turns at headlands and stationaries is shown. From the results, it emerged that the model is robust, since the validation with the measured data shows positive outcomes. Adopting the same model to forecast the behaviour along other operations performed with the same tractor, of which engine speed and torque are known, showed that the data are significantly representative.

Figure 5 - around here

From the results, it emerges the huge potential of this technology (CAN-bus + GPS + gas analyser) for environmental sustainability assessments and for the reduction of inputs use. The possibility of linking any collected data and of performing data processing permits to understand the behaviour of agricultural machinery along any operation and to study, from the mechanical point of view, how to reduce inputs use and outputs release. This means that the tractor, the coupling with the implement as well as the driver skills must adapt.

Concerning the model, the choice among the different options available in literature was mainly due to the possibility of evaluating engine-specific coefficients for higher reliability and of adopting the same equation for both fuel and emissions. However, there exist other modelling possibilities, such as that used by the ASABE (Grisso et al., 2014); in their study, authors showed both a general equation for fuel prediction and a specific one characterised by engine-specific coefficients, and concluded that this last works better than the general one. The reported equation also supports the outcomes of the model adopted in this study: the resulting average fuel consumption for the studied rotary harrowing operation is 9.68 $l\ h^{-1}$, which is in line with the selected model by Lindgren (2005) (9.90 $l\ h^{-1}$).

4 Impact assessment of harrowing using inventory data from different sources

In this section, the environmental impact of harrowing is assessed using a LCA approach and considering the data from different sources (e.g., database, ENVIAM, ENVIAM & data collected by means of CAN-bus, GPS and gas analyser).

4.1 Goal and scope

The goal of the study is to quantify how the reliability of inventory data can affect the environmental impact of field operations; to this purpose, the environmental impact of harrowing operation was assessed considering inventory data coming from different data sources.

The choice of rotary harrowing is due to the fact that it represents the most widespread secondary tillage operation performed for the seedbed preparation (Barthelemy et al., 1992; Šarauskis, 2014). In Central and Northern Europe, where the working depth of both primary and secondary soil tillage is shallow, harrowing plays an even more important role (Lindgren, 2004; Niero et al., 2015). For what concerns the importance of modern devices installed on tractors for the data collection, the results achieved for rotary harrowing can be upscaled to other tillage operations.

The research questions are:

- How reliable is the use of processes retrieved from commercial databases for LCA studies?
- Can the use of modern devices developed to map the engine performances be useful for the achievement of reliable inventory data?

4.2 Functional unit and system boundary

Usually, LCA studies focused on agricultural systems evaluate the environmental performances using different functional units; nevertheless, the most frequently utilised are: the cultivated area (ha) (Nemececk et al., 2015; Solinas et al., 2015) and the quantity of product such as the produced mass (e.g., Noya et al., 2015, Schmidt Rivera et al., 2017 tonne of grain cereals; Nikkhah et al., 2017 and Cerutti et al., 2016 for fruit), volume (e.g., Fusi et al., 2014 for wine, Negri et al., 2014 for biogas) or energy (e.g., Lijò et al., 2017; for the electricity from biomass).

In this LCA study, the secondary tillage operation is carried out with one single implement (a rotary harrow); therefore, no effects on crop yield are expected. The selected functional unit (FU) for the study is "1 ha tilled with an appropriate soil refinement for sowing and seed germination".

The system boundary involves the operation for secondary soil tillage (soil refinement with one or more repetitions on the same field). As reported in Fig. 6 all the different activities needed to till the soil are considered: effective work (moving forward while working in a straight direction); turns at the headlands (turning position); stationary (no change in position, mainly but not only with idling conditions).

Figure 6 around here

4.3 Description of the secondary soil tillage

Harrowing was performed in a sandy-loam soil by means of a rotary harrow (width 3.0 m, depth 100 mm, mass 890 kg) coupled with a 4WD tractor (82 kW, 4850 kg) belonging to the 3A Emissive Stage and equipped with EGR.

To highlight the differences related to inventory data reliability the following cases were compared:

- H-ECO: the harrowing process of the Ecoinvent database;
- H-ECO_FC: H-ECO modified considering the fuel consumption modelled by ENVIAM;
- H-ENVIAM_2: H-ECO modified considering fuel consumption and engine emissions modelled by ENVIAM[1] for a tractor belonging to Emissive Stage 2;
- H-ENVIAM_3A: H-ECO modified considering fuel consumption and engine emissions modelled by ENVIAM for a tractor belonging to Emissive Stage 3A;
- H-CANBUS: the rotary harrowing process assessed considering the variables processed during the field test using CAN-bus, GPS and gas analyser.

4.4 Life Cycle Inventory

The data sources are different among the different cases:

- H-ECO, only secondary data from the Ecoinvent database[2] were used (as reported in Table 3 and Table 4);
- H-ECO_FC, the main data come from Ecoinvent except for fuel consumption that was calculated by ENVIAM considering soil (e.g., texture) and geographical (e.g., slope and field shape) characteristics;

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[1] In ENVIAM, exhaust gases emissions are modelled following Schäffeler and Keller (2008) who quantify emissions as function of: (i) the Emissive Stage of the engine in accordance with the EU Directive 97/68/EC (and following amending ones: Directive 2010/26/EU, Directive 2010/22/EU), (ii) the maximum engine power of the tractor, (iii) the average engine load for the operation, (iv) the working time of the operation, (v) three correction factors depending on the deviation of effective engine load from the standard load on which the emission factor is based, on the tractor dynamic use and on the wear and tear of the engine. In ENVIAM emissions were quantified considering power, engine load and working time of each evaluated working phase in accordance with Reboul et al. (1964) and finally summed in a total value for the operation.

[2] Ecoinvent database is the most used database for LCA studies. With regard to agricultural systems, in the database are available processes of most field operations, energy supply, materials and substances, fertilisers and pesticides, etc.

- H-ENVIAM_2 and H-ENVIAM_3A, ENVIAM was used to assess fuel consumption and engine emissions as well as the amount of machine consumed during the operation. In particular, being both quantified with ENVIAM on the same operation, the difference between H-ENVIAM_2 and H-ENVIAM_3A is only due to the different emissive stage in order to show the benefit of having a tractor fleet composed of more modern tractors characterised by stricter engine exhaust gas emissive limits. More in detail, the tractor used for H-ENVIAM_3A is equipped with EGR (exhaust gas recirculation). The EGR is a system that diverts a portion of the exhaust gas back to the intake, where it is mixed with the fresh intake air and fed into the cylinder for combustion in order to reduce the NOx. The conversion of NO_X reaches up to 90%, mainly because the oxygen content per unit volume of intake air is lowered and hence NOx formation is reduced. Nonetheless, EGR entails an increase in fuel consumption (4-10%) (Volvo, 2010) for filter regeneration that occurs often due to the higher soot production. An increase of 5% was considered in this study;
- For the case H-CANBUS, primary data concerning fuel consumption, engine emissions and mass of machine were collected during the experimental tests and by means of interviews with technicians of the Swedish Machinery Testing Institute. The amount of consumed mass was calculated considering the duration of the field test (i.e. operation) and the tractor and implement life span.

When fuel consumption and engine emissions are calculated with ENVIAM, the resulting values are the sum of fuel consumption and engine emission that occur during each working state (effective work, turns, stationaries). This represents the same conceptual framework of values adopted in H-CANBUS.

Table 3 reports the main data concerning fuel consumption and engine emissions for the different cases.

Table 3 around here

The following parameters were considered: (i) theoretical life span, 12 and 10 years, respectively for the tractor and harrow, (ii) theoretical physical duration, 12000 and 2000 h, respectively for tractor and harrow (Lazzari and Mazzetto, 2005) and (iii) effective annual working time, 800 and 150 h, respectively for tractor and harrow (effective data collected from the interviews on the studied farm; this value is lower than the theoretical one).

Background data for raw materials extraction (e.g., fossil fuels and minerals), manufacture (e.g., tractors and implements), use, maintenance and final disposal of machinery as well as of buildings for machinery shelter were retrieved from Ecoinvent Database v3 (Althaus et al., 2007; Frischknecht et al., 2007; Jungbluth et al., 2007; Weidema et al., 2013). Table 4 reports the list of Ecoinvent processes utilised.

Table 4 around here

4.5 Life Cycle Impact Assessment

LCIA was carried out using updated characterisation factors from ReCiPe Midpoint methodology (Goedkoop et al., 2008) for the following impact categories: climate change (CC), ozone depletion (OD), terrestrial acidification (TA), freshwater eutrophication (FE), marine eutrophication (ME), photochemical oxidant formation (POF), particulate matter formation (PM), metal depletion (MD) and fossil depletion (FD).

5 Environmental results and discussion

5.1 Hotspots identification

Table 5 reports the repartition among the different inputs and outputs of environmental load associated to rotary harrowing in the different analysed cases. For each impact category, the environmental hotspots (i.e., the inputs and/or the outputs mainly affecting the environmental performance) can be identified. With small variations, the same hotspots can be identified in the different cases, in more detail:

- Engine emissions related to the combustion of diesel fuel are the main hotspot for: i) CC, due to the emissions of CO_2; ii) TA, due to the emissions of nitrogen oxides and sulphur dioxide; iii) POF, due to the emissions of nitrogen oxides and NMVOC, and iv) PM, due to the emissions of nitrogen oxides and particulates; instead they do not affect OD, TE, MD and FD.
- The production and maintenance of tractors and harrows are, by far, the main responsible for FE (about 85-94%) and MD (about 93-98%) and play a non-negligible role also on TA. For FE the impact is almost completely related to mine activities, while for MD to the consumption of iron ore, ferronickel and copper for equipment manufacturing. For TA the impact is related to the emissions of nitrogen oxides, sulphur dioxide and ammonia that take place during mine activities and during electricity production (electricity is consumed at the tractor and harrow manufacturing factories);
- Diesel production is the main responsible for OD and, although with a lesser extent, for FD. For OD, the impact is mainly due to the production of petroleum, while for FD to the consumption of crude oil.

- The shed for tractor and harrow storage plays a negligible role for all the evaluated impact categories.

Table 5 around here

5.2 Environmental impact comparison

Table 6 reports the environmental impact results of the studied operation with alternative data sources while in Fig. 7 a relative comparison is shown.

Figure 7 around here

Among the different cases, there is a huge variation of environmental results proving the importance of data inventory collection and estimation. This variation ranges from 10-18% in OD to 69% in MD. Compared to the process involved in the Ecoinvent database (H-ECO), except for H-ECO_FC, the other cases, based on inventory data directly measured (H-CANBUS) or estimated using ENVIAM (H-ENVIAM_2 and 3A), show a considerable lower environmental impact. This highlights the importance of site-specific inventory data: the uncritical use of the Ecoinvent process can involve a remarkable overestimation of the environmental impact.

Among the different cases, for all the 9 evaluated impact categories the environmental impact is the highest for H-ECO_FC; mainly, this is due to the higher fuel consumption. Between H-ECO and H-ECO_FC, where only FC differs, only negligible differences are highlighted, except for OD and FD that are the impact categories most effected by diesel consumption.

When changing both FC and the masses of tractor and operative machine consumed, great impact variations are recorded for TA, FE, ME, POF, PM and MD. In particular, on the categories affected by materials consumption (TA, FE, ME, POF, PM and MD), the calculation about the masses of materials consumed which is performed by means of ENVIAM and of the data collected during the field tests with CAN-bus and gas analyser involves an environmental impact considerably lower than those in which the assessment is based on Ecoinvent v3 database (H-ECO, H-ECO_FC).

The presence of H-ENVIAM_2, as expected, shows that the environmental impact for which an older tractor (i.e. not equipped with EGR) is responsible in relation to the technology for the treatment of engine emissions is higher. In more details, going from H-ENVIAM_2 to H-ENVIAM_3A, the reduction of NO_X emissions achieved with the EGR allows considerable benefits for the environmental categories deeply affected by these pollutants (TA, POF, ME and PM), but also a worsening of the environmental results for CC, OD and FD due to the slightly higher fuel consumption. For MD, the impact is much close due to the same amount of materials consumed. On TA, ME, POF and PM, H-CANBUS shows a higher impact compared with H-ENVIAM_3A because the engine exhaust gases emissions in ENVIAM were modelled as function of the normed emissive limit at the test bench, whilst on field these emissions may vary and be higher due to the field work conditions. A similar result and conclusion was retrieved from Lindvall et al. (2015) using the same tractor and from Larsson and Hansson (2011). On CC, OD and FD and slightly on FE and MD, H-ENVIAM_3A has a higher impact compared with H-CANBUS because a higher fuel consumption is modelled by ENVIAM rather than what is effectively measured on field with CAN-bus.

There is evidence that the different data sources bring different environmental impacts. In particular, modelling fuel consumption by taking into account the pedo-climatic variables and the field shape, a difference ranging between 10%-18% can be registered on CC and OD when compared with the environmental impact gathered from the database inventory data. Considering the CAN-bus measured data, the difference on CC even reaches 30% if compared with the Ecoinvent database unmodified case. This last feature causes an important overestimation of fuel consumption. Taking into account that is possible to optimise fuel consumption mainly by understanding what are the engine conditions for an attainable fuel use, additional improvements can be reached by adopting best driving practices. In the database, such enhancements cannot be evaluated. Also when evaluating the impact categories affected by material depletion, a strong difference emerges from the calculated value respect to the database average. In particular, considering the queried annual working time of tractor and implement (800 and 150 h, respectively), the environmental impact on FE and MD is 60 - 70% lower than in the database cases H-ECO and H-ECO_FC. This entails, similarly to fuel consumption, a considerable overestimation of the environmental load attributable to materials use and depletion along the machinery life span. On the opposite, from the results emerges that modelling engine exhaust gases in accordance with the normed emissive limits instead of using the collected data while working on field causes an underestimation of the environmental impact, mainly on those impact categories mostly affected by engine pollutants (range between 45 - 65% on TA, POF and PM respect to the Ecoinvent not modified process). Additionally, the monitoring of exhaust gases emissions on field is a very interesting possibility because collecting data on field represents a step forward in defining the normative emissive limits, although with engine and operating variability. Attributing emissions to working states showed that, commonly, considerable and consistent differences emerge along the operation: with stationary-idling conditions and transient conditions, exhaust emissions of NO_X, CO and CO_2 considerably increased and represented up to 15% of the total working time.

5.2.1 Uncertainty analysis

To test the robustness of the comparative LCA study, an uncertainty analysis was performed using a Monte Carlo statistical technique. Two cases were selected for the comparison: H-CANBUS and H-ENVIAM_3A, both the cases consider a tractor equipped with a EGR system, therefore, the impact differences are fully related to data source. Table 7 reports the results of the comparison considering mean value and standard deviation, while in Fig. 8 are shown the results of the uncertainty analysis comparing H_ENVIAM_3A and H_CANBUS for the evaluated impact categories. The bars on the left represent the probability that the environmental impact of H-CANBUS is lower than H-ENVIAM_3A, while those on the right mean the opposite (the environmental impact of H-CANBUS is higher than H-ENVIAM_3A).

Table 7 around here

Figure 8 around here

The results of the uncertainty analysis confirm that the environmental impacts of H-CANBUS, gathered from data directly collected on field, are smaller than those of the case H-ENVIAM_3A for CC (level of statistical significance > 88%) and for OD and FD with a level of statistical significance > 70%. On FE and MD, the statistical significance is 53% and 51%, respectively. The environmental impact results are higher in H-CANBUS than in H-ENVIAM_3A with a level of statistical significance > 96% for TA, POF and PM and > 94% for ME.
Therefore, the results show that the uncertainty due to the selection of the data source associated with the cumulative effect of model imprecision, inputs and data variability mainly affects FE, MD and FD (production and maintenance of machinery and diesel production), whilst other impact categories show a reduced uncertainty level.

6 Conclusions

This study has shown that the reliability of inventories carried out with local variables is very important, since the inventory data can deeply affect the downstream results of the study. Nowadays, with the adoption of modern technologies on agricultural tractors and modern machinery in general (CAN-bus, GPS, emissions analyser and analysis software), the collection of primary data regarding mechanisation of field operations is getting easier. A positive result is gained by inventories for environmental impact assessments, since they can be filled with high reliability. In particular, engine-specific equations able to describe fuel consumption and exhaust gases emissions depending on torque and engine speed and any relevant available information can be developed for the studied engine.

With the collected and collectable data, an interesting present and near future research regards the improvement of knowledge on tractors and their variables while working directly on field. As shown here, it is possible to measure data in the field, to process them into different working states that can be analysed one by one and to use them to quantify the environmental impact of the operation with higher reliability than the data present in the databases used for LCA studies. From this analysis, it has emerged that the uncritical use of databases should be avoided particularly when the LCA study focuses on agricultural systems and, above all on field operations. Moreover, the application of LCA to agricultural mechanisation highlights interesting possibilities and provides useful results to guide stakeholders, users and farmers to understand complex aspects that should be analysed in their entirety and not limited to single facets.

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FIGURE CAPTIONS

Fig. 1 – Methodological framework for the study: primary and secondary local reliable data are used for the inventory fulfilment of a field operation and the environmental impact is subsequently quantified through Life Cycle Assessment approach.

Fig. 2 - Schematic flow of ENVIAM steps.

Fig. 3 - Valtra N101 tractor with the implemented system to collect exhaust gases for the gases analyser.

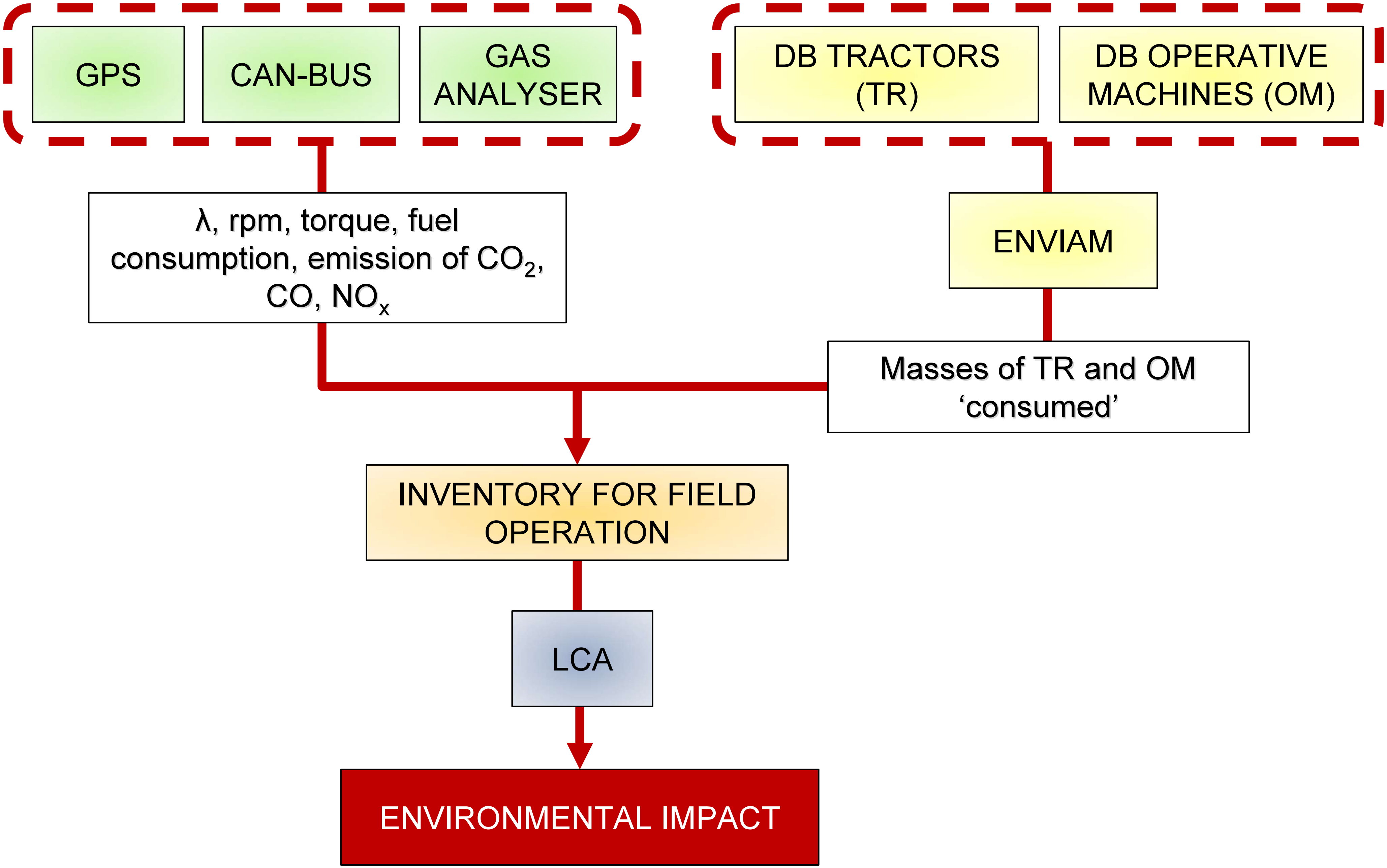
Fig. 4 - Working states on part of the field worked with the rotary harrow, obtained thanks to the processing of the tractor GPS coordinates. Red represents the effective work, green is the turn on headlands and blue is stationary position with no-work ongoing (online version of the study).

Fig. 5 - Regression calculated for fuel consumption in the working states of rows (effective work), turns and stationaries.

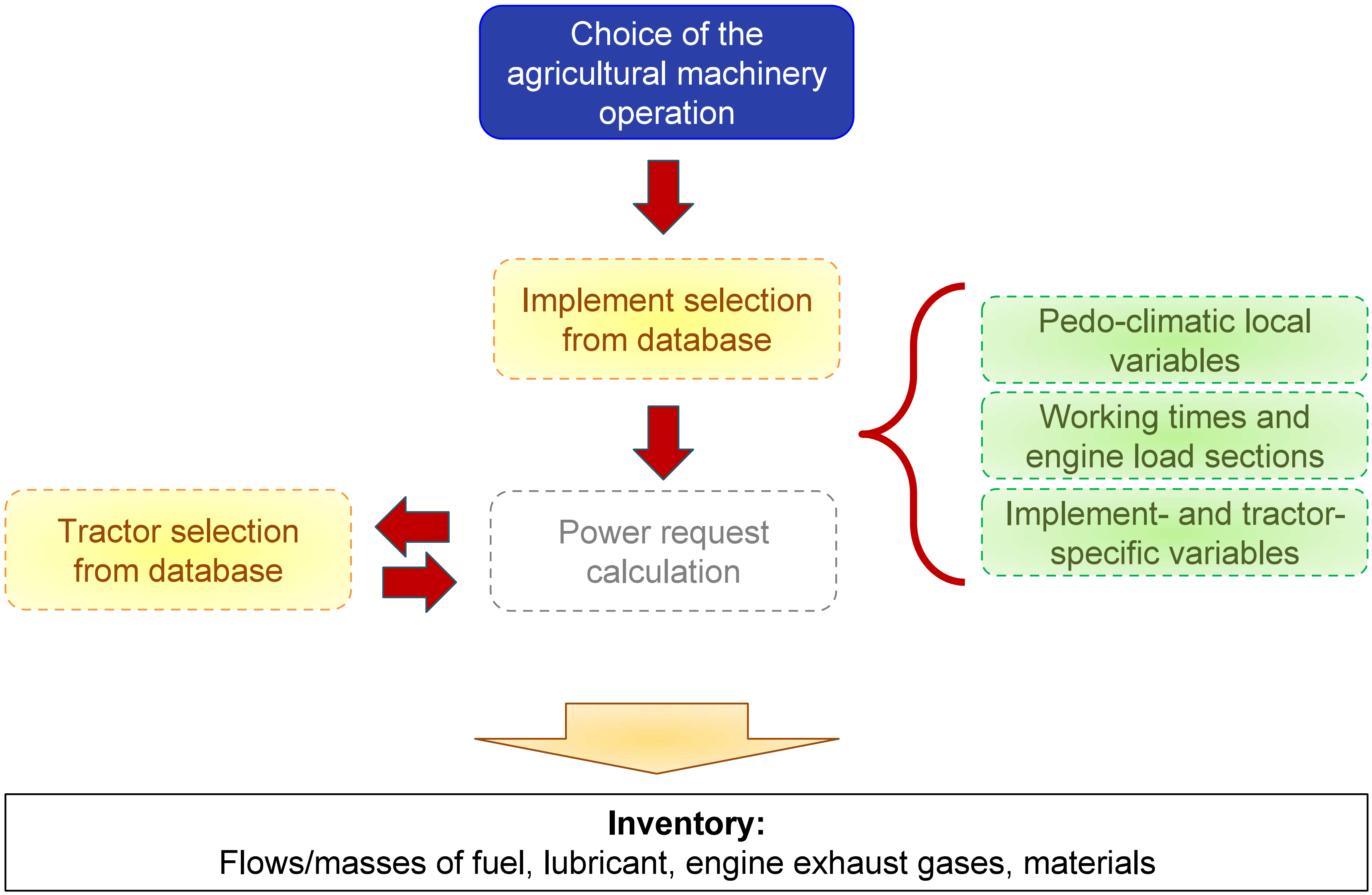
Fig. 6 – System boundary for the rotary harrowing operation.

Fig. 7 – Environmental impact results for the rotary harrowing quantified with the different data sources.

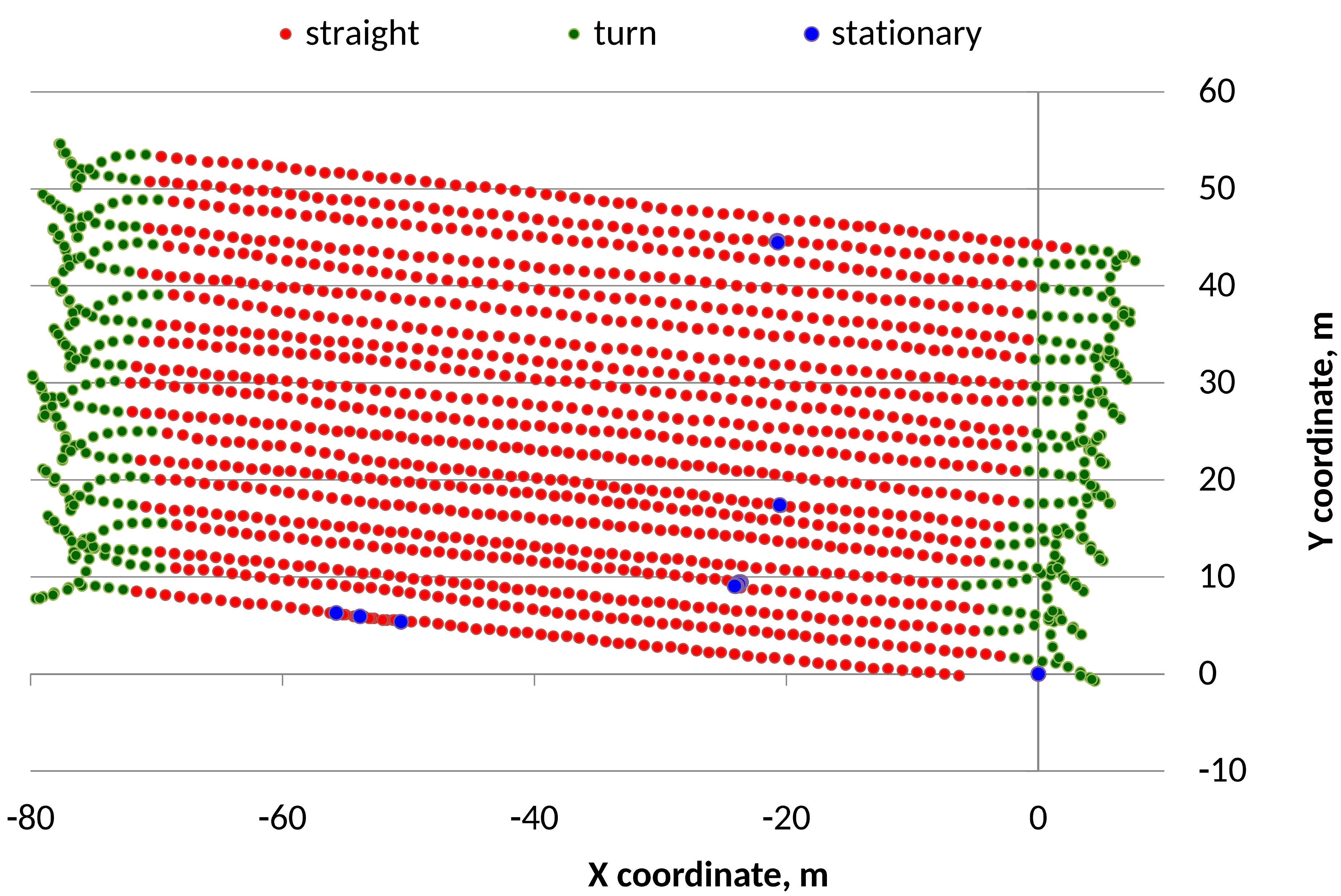
Fig. 8 – Results of the uncertainty analysis for the comparison between the two cases carried out with a tractor equipped with a EGR.

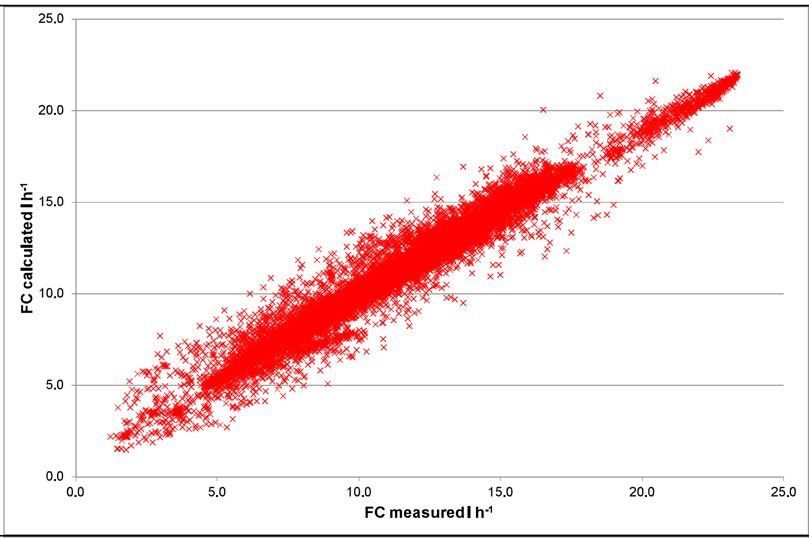
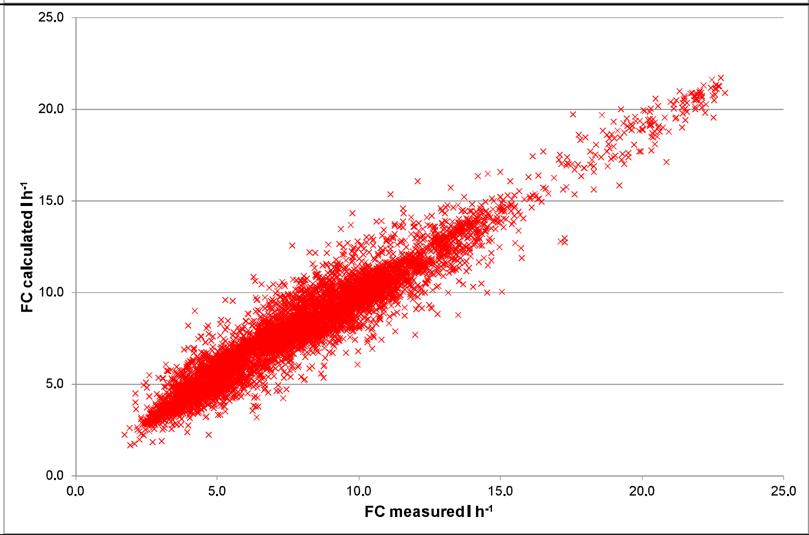
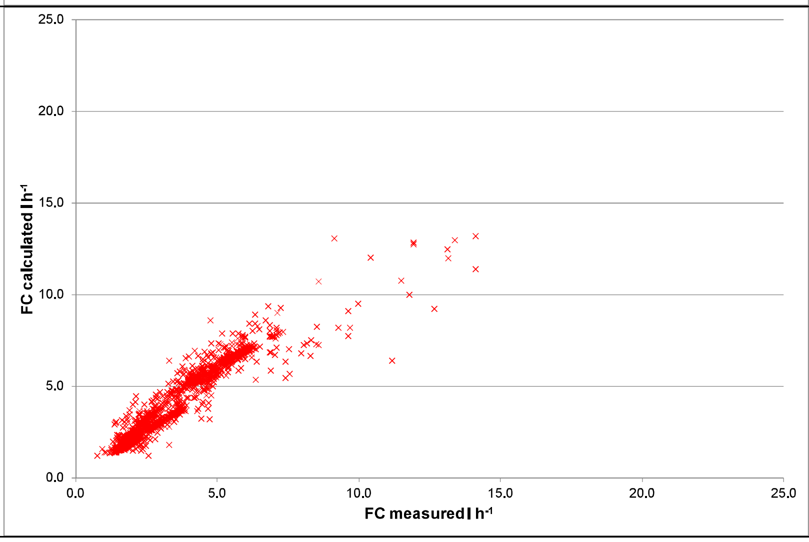


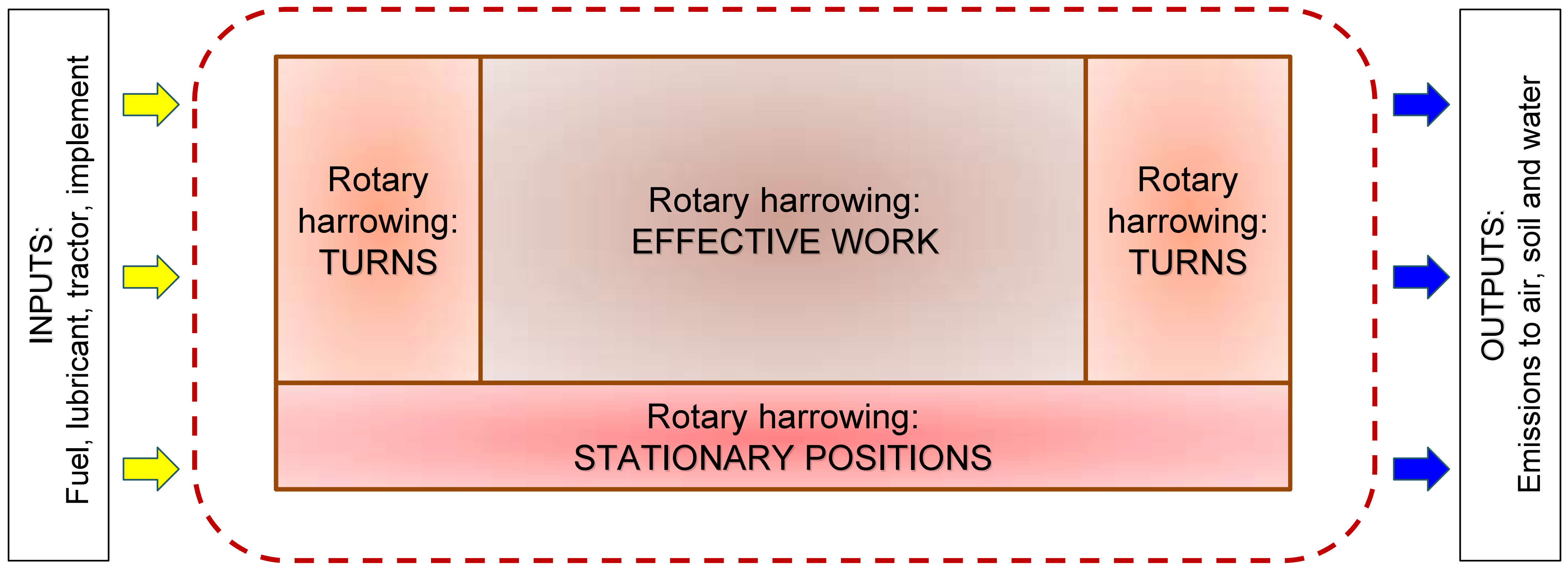
GPS
CAN-BUS
GAS ANALYSER
DB TRACTORS (TR)
DB OPERATIVE MACHINES (OM)
λ, rpm, torque, fuel consumption, emission of CO_2, CO, NO_x
ENVIAM
Masses of TR and OM 'consumed'
INVENTORY FOR FIELD OPERATION
LCA
ENVIRONMENTAL IMPACT

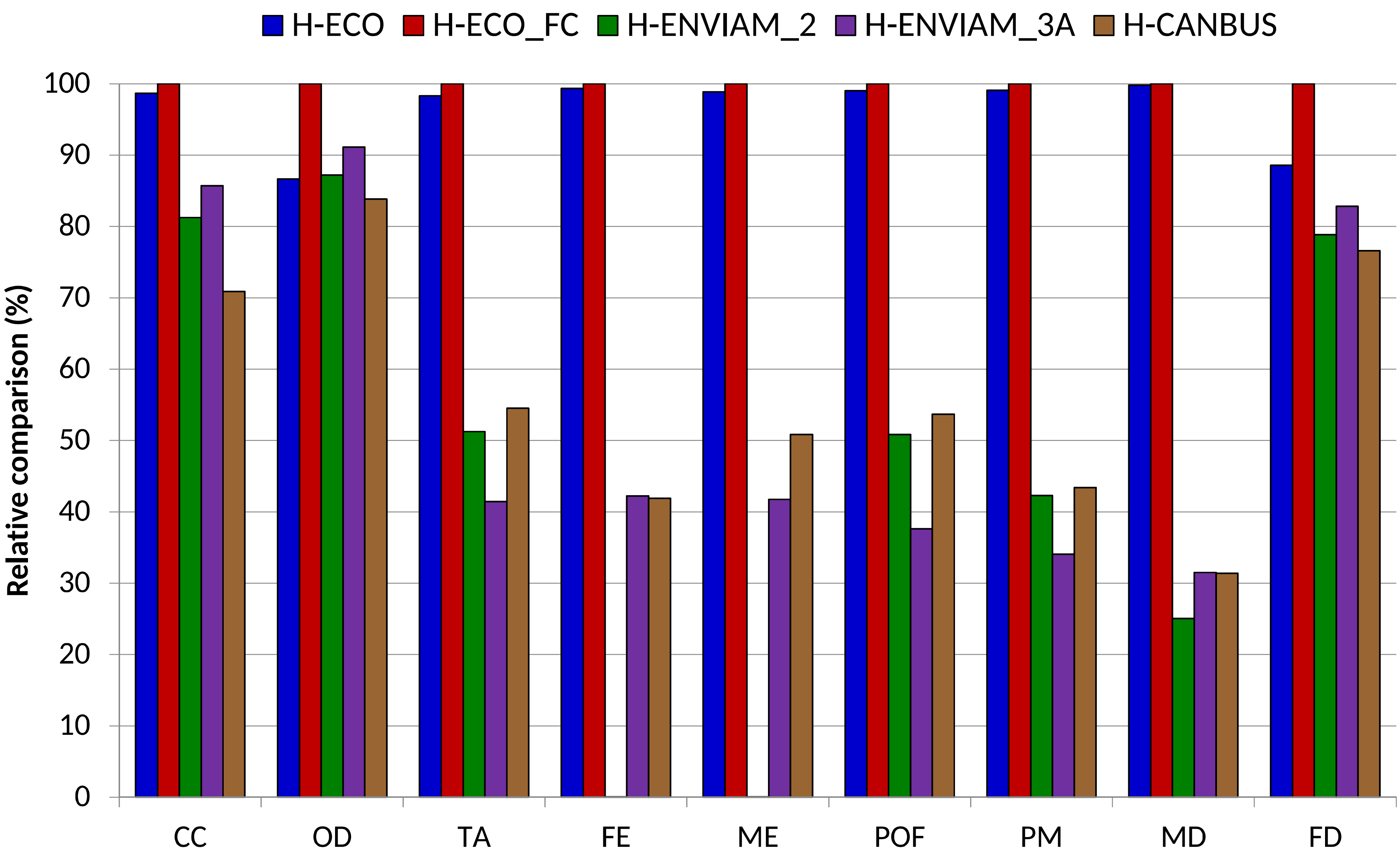

Choice of the agricultural machinery operation
Implement selection from database
Pedo-climatic local variables
Working times and engine load sections
Implement- and tractor-specific variables
Tractor selection from database
Power request calculation
Inventory:
Flows/masses of fuel, lubricant, engine exhaust gases, materials

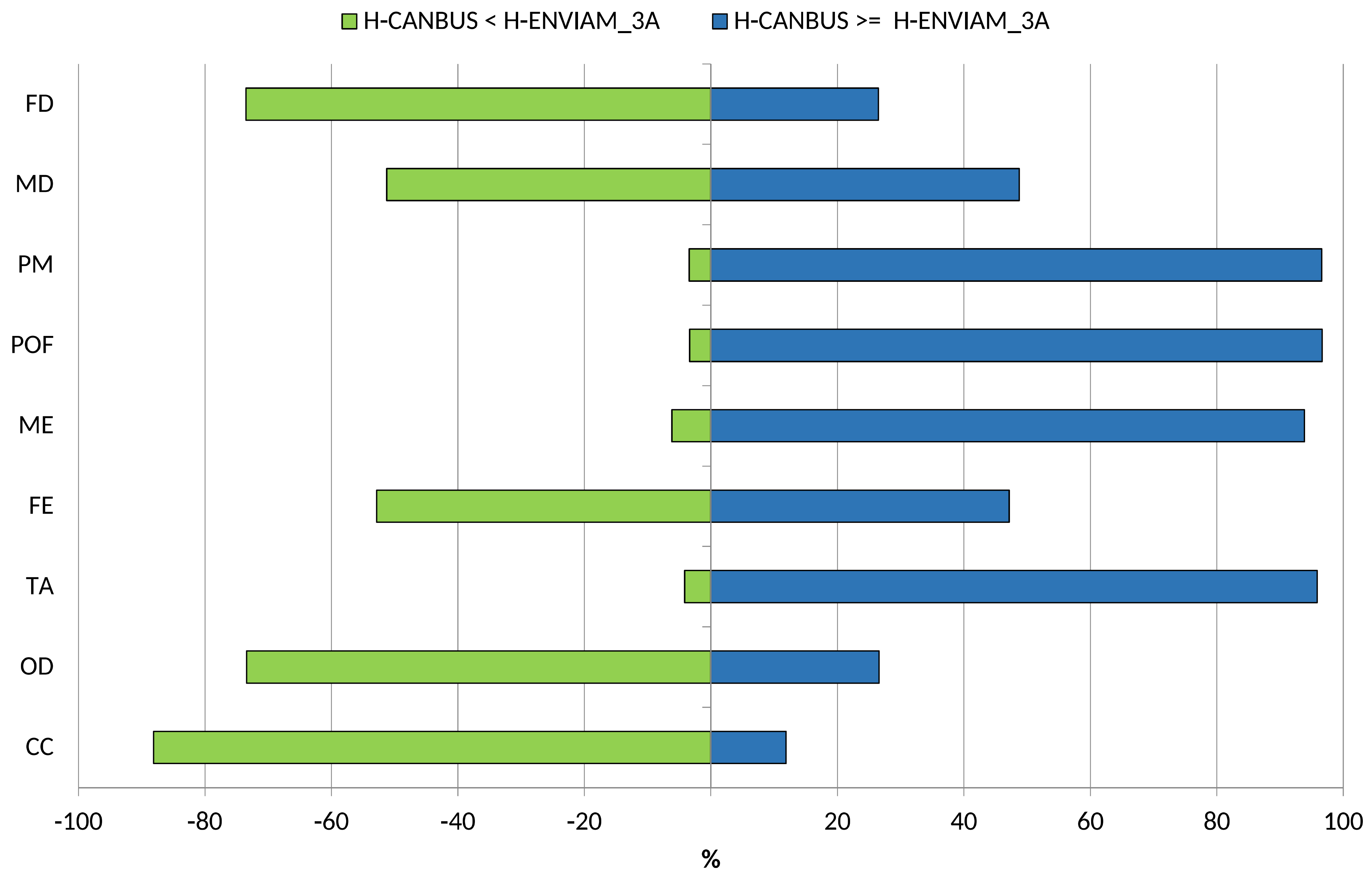

BIOGAS


straight
turn
stationary
60
50
40
30
20
10
0
-10
-80
-60
-40
-20
0
X coordinate, m
Y coordinate, m

Rows ($R^2 = 0.97$)	
Turns ($R^2 = 0.92$)	
Stationaries ($R^2 = 0.95$)	


INPUTS:
Fuel, lubricant, tractor, implement
Rotary harrowing: TURNS
Rotary harrowing: EFFECTIVE WORK
Rotary harrowing: TURNS
Rotary harrowing: STATIONARY POSITIONS
OUTPUTS:
Emissions to air, soil and water


H-ECO
H-ECO_FC
H-ENVIAM_2
H-ENVIAM_3A
H-CANBUS
Relative comparison (%)
100
90
80
70
60
50
40
30
20
10
0
CC
OD
TA
FE
ME
POF
PM
MD
FD


H-CANBUS < H-ENVIAM_3A
H-CANBUS >= H-ENVIAM_3A
FD
MD
PM
POF
ME
FE
TA
OD
CC
-100
-80
-60
-40
-20
20
40
60
80
100
%

TABLES

Table 1 – Average values for each working state for fuel consumption (kg ha^{-1}), emissions of CO_2, CO and NO_X (g ha^{-1}), absorbed engine power (kW) and engine load (%). In brackets are reported values for sample standard deviation.

Working state	Fuel consumption (kg ha^{-1})	Emission			Average engine power (kW)	Average engine load (%)
		CO_2 (kg ha^{-1})	CO (g ha^{-1})	NO_X (g ha^{-1})		
Effective time (rows)	8.00 (1.72)	21.457 (14.256)	6.69 (7.22)	160.69 (105.41)	33.2 (7.3)	39.8 (0.09)
Turns at headlands	2.98 (2.25)	7.999 (11.236)	2.50 (6.17)	59.91 (87.30)	19.9 (9.0)	23.9 (0.10)
Stationary	1.52 (1.53)	4.072 (6.394)	1.27 (3.95)	30.50 (50.06)	8.0 (3.7)	9.6 (0.04)
Total	11.50	33.528	10.46	251.10	--	--

Table 2 – Model engine-specific coefficients calculated for tractor Valtra N101.

Engine-specific coefficients	**Variable**			
	Fuel consumption	**CO_2 emission**	**CO emission**	**NO_X emission**
c_1	-2.29×10^{-3}	-5.57×10^{0}	4.33×10^{-2}	-3.95×10^{-1}
c_2	4.35×10^{-6}	1.12×10^{-2}	-6.77×10^{-5}	6.27×10^{-4}
c_3	-1.10×10^{-9}	-2.90×10^{-6}	2.67×10^{-8}	-2.14×10^{-7}
c_4	5.92×10^{-5}	1.49×10^{-1}	-1.52×10^{-4}	5.74×10^{-3}
c_5	-5.15×10^{-8}	-1.26×10^{-4}	2.80×10^{-7}	-7.04×10^{-6}
c_6	1.91×10^{-11}	4.81×10^{-8}	-1.46×10^{-10}	2.38×10^{-9}
c_7	-1.18×10^{-7}	-3.04×10^{-4}	2.66×10^{-7}	-1.19×10^{-5}
c_8	1.64×10^{-10}	4.27×10^{-7}	-5.97×10^{-10}	1.64×10^{-8}
c_9	-5.35×10^{-14}	-1.42×10^{-10}	4.31×10^{-13}	-5.85×10^{-12}

Table 3 – Main inventory data for the different cases considered for harrowing ([1] data from Ecoinvent database).

Case	Work state	Fuel consumption (kg ha^{-1})	CO_2 emission (kg ha^{-1})	CO emission (g ha^{-1})	NO_X emission (g ha^{-1})
H-ECO	Effective work	--	--	--	--
	Turn				
	Stationary				
	Total	11.5[1]	35.700[1]	92.4[1]	467[1]
H-ECO_FC	Effective work	9.67	--	--	--
	Turn	3.13			
	Stationary	0.94			
	Total	13.7	35.700[1]	92.4[1]	467[1]
H-ENVIAM_2	Effective work	9.57	28.952	49.11	170.39
	Turn	3.39	9.388	13.32	46.23
	Stationary	0.12	2.817	3.74	12.97
	Total	13.0	41.109	66.2	229.6
H-ENVIAM_3A	Effective work	9.57	30.476	41.82	99.77
	Turn	3.39	9.858	11.35	27.07
	Stationary	0.12	2.965	3.18	7.59
	Total	13.7	43.299	56.3	134.4
H-CANBUS	Effective work	See Table 1			
	Turn				
	Stationary				
	Total				

Table 4 – Processes retrieved from Ecoinvent database.

Ecoinvent Process	Note
Tillage, harrowing, by rotary harrow {CH}| processing | Alloc Def, U	Corresponds to H_ECO
Tractor, 4-wheel, agricultural {GLO}| market for | Alloc Def, U	Amount of consumed tractors, the value reported in the Ecoinvent harrowing process was modified in H_ENVIAM_2, H_ENVIAM_3A and H-CANBUS
Agricultural machinery, tillage {GLO}| market for | Alloc Def, U	Amount of consumed implement, the value reported in the Ecoinvent harrowing process was modified in H_ENVIAM_2, H_ENVIAM_3A and H-CANBUS
Shed {GLO}| market for | Alloc Def, U	Shed
Diesel {Europe without Switzerland}| market for | Alloc Def, U	Diesel consumption, the value reported in the Ecoinvent harrowing process was modified in H_ECO-FC, H_ENVIAM_2, H_ENVIAM_3A and H-CANBUS

Table 5 – Hotspots identification for the different impact categories

Impact category	Case	Engine emissions	Tractor prod&main	Machinery prod&main	Shed	Diesel prod
CC	H-ECO	52.60%	7.60%	31.92%	0.83%	7.04%
	H-ECO_FC	51.90%	7.50%	31.50%	0.82%	8.28%
	H-ENVIAM_2	73.43%	8.80%	7.15%	0.96%	9.66%
	H-ENVIAM_3A	73.43%	8.80%	7.15%	0.96%	9.66%
	CANBUS	68.90%	10.64%	8.64%	1.16%	10.66%
OD	H-ECO	0.00%	6.20%	12.76%	0.54%	80.51%
	H-ECO_FC	0.00%	5.37%	11.05%	0.46%	83.11%
	H-ENVIAM_2	0.00%	5.93%	2.36%	0.51%	91.20%
	H-ENVIAM_3A	0.00%	5.93%	2.36%	0.51%	91.20%
	CANBUS	0.00%	6.44%	2.56%	0.55%	90.44%
TA	H-ECO	60.74%	6.30%	23.31%	0.54%	9.11%
	H-ECO_FC	59.70%	6.20%	22.91%	0.53%	10.67%
	H-ENVIAM_2	58.79%	11.73%	8.40%	0.99%	20.10%
	H-ENVIAM_3A	47.23%	15.02%	10.75%	1.27%	25.73%
	CANBUS	61.57%	11.42%	8.18%	0.97%	17.86%
FE	H-ECO	0.00%	22.77%	72.32%	1.51%	3.41%
	H-ECO_FC	0.00%	22.62%	71.85%	1.50%	4.03%
	H-ENVIAM_2	0.00%	53.81%	33.09%	3.55%	9.55%
	H-ENVIAM_3A	0.00%	53.81%	33.09%	3.55%	9.55%
	CANBUS	0.00%	54.26%	33.37%	3.58%	8.79%
ME	H-ECO	39.36%	13.90%	38.48%	2.14%	6.12%
	H-ECO_FC	38.90%	13.73%	38.04%	2.12%	7.21%
	H-ENVIAM_2	38.56%	27.78%	14.89%	4.26%	14.51%
	H-ENVIAM_3A	26.90%	33.05%	17.72%	5.07%	17.26%
	CANBUS	41.19%	27.15%	14.55%	4.17%	12.94%
POF	H-ECO	73.26%	4.18%	17.04%	0.34%	5.18%
	H-ECO_FC	72.54%	4.14%	16.87%	0.34%	6.11%
	H-ENVIAM_2	73.16%	8.04%	6.34%	0.65%	11.81%
	H-ENVIAM_3A	63.07%	11.07%	8.73%	0.90%	16.24%
	CANBUS	75.13%	7.75%	6.11%	0.63%	10.38%
PM	H-ECO	65.71%	4.83%	24.19%	0.46%	4.81%
	H-ECO_FC	65.11%	4.79%	23.97%	0.45%	5.68%
	H-ENVIAM_2	62.12%	11.68%	11.32%	1.10%	13.78%
	H-ENVIAM_3A	54.15%	14.14%	13.70%	1.33%	16.68%
	CANBUS	65.19%	11.09%	10.74%	1.04%	11.94%
MD	H-ECO	0.00%	12.92%	85.29%	0.76%	1.03%
	H-ECO_FC	0.00%	12.89%	85.12%	0.76%	1.23%
	H-ENVIAM_2	0.00%	41.13%	52.56%	2.42%	3.89%
	H-ENVIAM_3A	0.00%	41.13%	52.56%	2.42%	3.89%
	CANBUS	0.00%	41.27%	52.74%	2.42%	3.56%
FD	H-ECO	0.00%	7.88%	24.14%	0.53%	67.45%
	H-ECO_FC	0.00%	6.98%	21.38%	0.47%	71.17%
	H-ENVIAM_2	0.00%	8.47%	5.02%	0.57%	85.94%
	H-ENVIAM_3A	0.00%	8.47%	5.02%	0.57%	85.94%
	CANBUS	0.00%	9.16%	5.43%	0.62%	84.79%

Table 6 – Comparison among the different cases (FU = 1 ha)

Impact	Unit	H-ECO	H-ECO_FC	H-ENVIAM_2	H-ENVIAM_3A	H-CANBUS
CC	kg [CO_2 eq]	68.728	69.654	59.692	59.692	49.369
OD	mg [CFC-11 eq]	8.771	10.122	9.223	9.223	8.487
TA	kg [SO2 eq]	0.451	0.458	0.243	0.190	0.250
FE	g [P eq]	12.571	12.653	5.344	5.344	5.300
ME	g [N eq]	46.331	46.874	23.290	19.577	23.830
POF	kg [NMVOC]	0.670	0.677	0.350	0.255	0.363
PM	kg [PM10 eq]	0.255	0.258	0.106	0.088	0.112
MD	kg [Fe eq]	15.443	15.474	4.875	4.875	4.858
FD	kg [oil eq]	19.535	22.056	18.265	18.265	16.890

Table 7 – Mean value and standard deviation for the evaluated cases.

Impact category	Mean value	Standard deviation
CC	-10.294	8.876
FD	-1.351	2.227
FE	-4.47×10^{-5}	0.00056
ME	0.0042	0.0029
MD	-0.023	0.476
OD	-7.36×10^{-7}	1.39×10^{-6}
PM	0.0241	0.014
POF	0.1086	0.0637
TA	0.0596	0.0365