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Electric autonomous tractors in Swedish agriculture

A systems analysis of economic, environmental and performance effects

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Abstract

Use of battery-electric vehicles has become common in different sectors, as a measure to reduce greenhouse gas emissions. Driveline electrification in agricultural machinery could reduce emissions and increase driveline efficiency, but implementation has been hindered by the low energy-carrying capacity of batteries compared with conventional fuels. Combining battery-electric drivelines and autonomous operation would provide important synergies by mitigating or eliminating many of negative aspects of electrification, while retaining the benefits from both systems.

This thesis evaluated the potential and analysed the intricate workings of a battery-based autonomous electric vehicle system by applying systems analysis, economic analysis and life cycle assessment, through simulations and modelling. The vehicle system was evaluated on a theoretical Swedish grain farm of 200 ha using a conventional cropping system. Soil compaction, battery ageing, queueing dynamics, field trafficability, energy storage and weather effects were all included in simulations. This allowed comparison of performance, cost and environmental impacts for a conventional fieldwork tractor and a system with several smaller autonomous battery-electric tractors.

The evaluation showed that the autonomous electric tractors were able to match or exceed the daily work rate of the conventional tractor, while reducing energy use (by 47-75%), lowering annual costs (by 32-37%) and reducing soil compaction. The environmental impact was generally also lower, with up to a 74% reduction in greenhouse gas emissions over the system’s life cycle. These results indicate great potential for autonomous electric tractors in future agricultural fieldwork, as combining the electric driveline and autonomous technologies allowed the benefits from both to be used to greater effect than either by itself.

Keywords: Agriculture, autonomy, economy, battery-electric vehicles, life cycle assessment, modelling, simulation, soil compaction, tractor

Elektriska, autonoma traktorer i svenskt lantbruk

Sammanfattning

Elektriska fordon är en vanlig åtgärd för att minska utsläppen av växthusgaser i olika sektorer. Elektrifiering av lantbruksmaskiner har potential att minska utsläppen och öka verkningsgraden i fordonens drivlinor, men på grund av låg energidensitet i batterier jämfört med konventionella fordonsbränslen har introduktionstakten varit låg. Genom att kombinera batterielektriska fordon med autonom teknik kan man uppnå synergieffekter, vilket gör det möjligt att minska eller eliminera nackdelarna med elektriska fordon och samtidigt nyttja fördelarna hos båda systemen.

Denna avhandling syftar till att utvärdera potentialen och analysera de komplexa sambanden hos system av autonoma, elektriska fordon med hjälp av systemanalys, ekonomiska kalkyler och livscykelanalyser utförda i modeller och simuleringar. Fordonssystemet utvärderades på en teoretisk svensk spannmålsgård på 200 hektar, där en konventionell odlingsmetod simulerades. Markpackning, batteriåldrande, kö-dynamik, körbarhet på fält, energilager och väderberoende inkluderades i simuleringarna. Detta möjliggjorde jämförelsen av arbetskapacitet, kostnader och miljöpåverkan mellan en konventionell traktor och ett system bestående av flera mindre, autonoma eltraktorer.

Eltraktorer visades kunna ha liknande eller högre daglig arbetstakt än konventionella traktorer, samtidigt som dem reducerade energianvändningen (41-75%), den totala årliga kostnaden (32-37%) och minskade markpackningen. Generellt minskade miljöpåverkan, med en minskning av växthusgasutsläppen med upp till 74% över hela livscykeln. Dessa resultat visade på den stora potentialen hos autonoma, elektriska traktorer i lantbrukets fältarbeten. Genom att kombinera teknologierna kunde fördelarna från båda systemen utnyttjas på ett bättre sätt än var för sig.

Nyckelord: Autonomi, batterifordon, ekonomi, lantbruk, livscykelanalys, modellering, markpackning, simulering, traktor

Dedication

Dedicated to everyone who works to make the world a better place, in ways big or small.

"Step-by-step, year-by-year, the world is improving. Not on every single measure every single year, but as a rule. Though the world faces huge challenges, we have made tremendous progress. This is the fact-based worldview."

-Hans Rosling, *Factfulness*

Contents

List of publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I. **Lagnelöv, O**., Larsson, G., Nilsson, D., Larsolle, A. & Hansson, P.-A. (2020). Performance comparison of charging systems for autonomous electric field tractors using dynamic simulation. *Biosystems Engineering* 194, 121-137.

II. **Lagnelöv, O**., Dhillon, S., Larsson, G., Nilsson, D., Larsolle, A. & Hansson, P.-A. (2021). Cost analysis of autonomous battery electric field tractors in agriculture. *Biosystems Engineering* 204, 358-376.

III. Larsson, G., **Lagnelöv, O**., Larsolle, A., Hansson, P-A. (2022). What role does energy storage have for electric agricultural vehicle systems? (Manuscript)

IV. **Lagnelöv, O**., Larsson, G., Larsolle, A. & Hansson, P.-A. (2021). Life cycle assessment of autonomous electric field tractors in Swedish agriculture. *Sustainability* 13, 11285.

V. **Lagnelöv, O**., Larsson, G., Larsolle, A. & Hansson, P.-A. (2023). Impact of lowered vehicle weight of electric autonomous tractors in a systems perspective. *Smart Agricultural Technology* 4, 100156.

Papers I, II, IV & V are reproduced with the permission of the publishers.

The contribution of Oscar Lagnelöv to the papers included in this thesis was as follows:

I. Planned the paper together with the co-authors. Performed the model building, simulation and data analysis. Wrote the paper with support from the co-authors.

II. Planned the paper and analysis together with the co-authors. Performed the modelling, simulation, calculations and data analysis. Wrote the paper with support from the co-authors.

III. Performed part of the modelling and data analysis. Co-wrote the paper.

IV. Planned the paper together with the co-authors. Performed the model building, simulation and data analysis. Wrote the paper with support from the co-authors.

V. Planned the paper and analysis with the co-authors. Performed the simulation, calculations and data analysis. Wrote the paper with support from the co-authors.

Abbreviations

BES	Battery exchange system
BED	Battery-electric drive
BEV	Battery-electric vehicle
BMS	Battery management system
CC	Conductive charging
CC/CV	Constant current/constant voltage (charging method)
DES	Discrete-event simulation
DoD	Depth of discharge
EoL	End of life
GHG	Greenhouse gases
ICE	Internal combustion engine
LCA	Life cycle assessment
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
NCA	Lithium nickel cobalt aluminium oxide (battery)
PMSM	Permanent magnet synchronous motor
PV	Photovoltaic (solar cells)
SoC	State of charge
SoH	State of health

1. Introduction

Agriculture is generally considered to be a green sector, due to the nature of agricultural production and its close symbiotic relationship with nature. However, agriculture has an impact on the climate and other parts of the environment and is sensitive to changes in both of these (Smith et al., 2014). Long-term global food production will require effective and sustainable agriculture, so a truly green agriculture sector with limited environmental impact and resilience to changes is an important goal for the near future.

Agricultural machinery is a small contributor to the total environmental impacts of agriculture, producing roughly 1% of global greenhouse gas (GHG) emissions in 2014, while agriculture in total produced 21-24% (Smith et al., 2014; Tubiello et al., 2015). Machinery emissions are easier to reduce than those from other emissions hotspots, since reducing the impacts from *e.g.* land use, fertilisers, N_2O and field emissions may require land-use changes or ambitious yield improvements.

One technical solution to reduce emissions is driveline electrification. Electric drivelines have higher driveline efficiency, require less maintenance and have a reduced fuel import demand, and are therefore being considered as a viable solution for mobile non-road machinery, such as agricultural tractors, as well as road vehicles. Electrification of vehicle drivelines is now a commonly proposed solution for reducing vehicle emissions, due to technical improvements in drivelines, chargers and batteries, political ambitions to cease using fossil fuels and reduced cost of driveline components, most notably the price of batteries, which has dropped by over 90% in the past 20 years (IPCC, 2022). Electrification has particular potential for GHG emissions reduction when low-emission electricity is available, as is the case in Sweden (Swedish Environmental Protection Agency, 2020).

There are challenges to using electric tractors in conventional fieldwork, in particular the low amount of energy carried by the vehicles. Conventional diesel tractors generally carry enough fuel to perform a day's worth of fieldwork, which is practical since it fits with driver schedules and means little to no unproductive time due to transport between field and farm. Replacing conventional tractors by simply changing the driveline would lead to fieldwork times shorter than a day's work before recharging, resulting in sub-optimal use of the driver, who often represents a large part of the operating costs in modern agriculture. It would also lead to long recharge times for the batteries, *i.e.* yet more unproductive time not spent working (Caban et al., 2018). This increase in non-productive time would delay completion of fieldwork, leading to sub-optimal crop establishment, fertilisation and pesticide application. Alternatively, several tractors and/or drivers could be hired or a very large battery could be used, which again would lead to high costs. In order for electric tractor systems to be successful, these challenges need to be resolved (Beligoj et al., 2022).

A solution to some of these challenges is autonomous operation, where the tractors operate without a driver in the cab. This would decouple the productivity of the tractors from the schedule of the driver and negate most of the challenges posed by electric drivelines, while retaining the benefits. It would allow the tractor to work all suitable hours of the day, and not only when the driver is scheduled to work. It would also reduce the negative effects of carrying a smaller amount of energy, since there is no driver who needs to be paid while the recharging takes place. In addition, it would enable the use of multiple lighter tractors instead of the single large machine used in conventional systems. Self-driving tractors are already being introduced on the market and are commonly cited as an essential factor in the next step of increased agricultural productivity.

Some field tests have been performed on electric and/or autonomous tractors and multiple large manufacturers are testing prototypes, but there are very few large-scale studies available and there is a general lack of empirical data (Gil et al., 2023; Rahmadian & Widyartono, 2020; Scolaro et al., 2021). To evaluate the potential effects of introduction of autonomous battery-electric vehicles on Swedish agriculture, simulations and system analysis are required. By using discrete-event simulation, discrete occurrences can be accounted for, while by using a varied interval of parameters (such as years), variances and extreme values can be explored. Since a system change to autonomous battery-electric vehicles would affect multiple aspects of the system, multi-level analysis with several goal variables would be required. Economic viability and environmental impact would need to be explored, through annual cost of operation and life cycle analysis (LCA), respectively.

The aim in this thesis was to bridge the gap between the established theoretical understanding of the individual parts of the system (autonomous vehicles, electric vehicles, battery technology, agricultural cropping systems) and empirical data emerging from field tests and real-world validation, by combining these in a Swedish context.

2. Aim and scope

2.1 Aim and objectives

The overall aim of the work described in this thesis was to improve understanding of the effects of introducing autonomous battery-electric tractors into Swedish agriculture in terms of operation, economics and environmental impact, compared with conventional manned diesel tractors. The following research questions were addressed:

- Can battery-electric tractors provide comparable work rate to diesel tractors and, if so, under what circumstances?
- Can autonomous battery-electric tractors reduce the environmental impact of agricultural machinery use in Sweden?
- Can autonomous battery-electric tractors do the above while being economically competitive compared with conventional tractors?
- What are the important technology choices and can they be optimised for Swedish agriculture?

Specific objectives of the work were to:

- Study the energy efficiency, use and storage of energy for autonomous battery-electric tractors (**Papers I-III**).
- Investigate technology choices that can contribute to the development of optimal systems for autonomous battery-electric tractors (**Papers I & III**).
- Analyse how different technology choices and system structures affect work rate (**Papers I & II**), cost (**Paper II**) and resource use (**Paper IV**).
- Quantify the resulting environmental and climate impacts through systems analysis and LCA (**Papers IV & V**).

2.2 Scope

The work in this thesis encompassed different vehicle systems, all centred on the theoretical framework of a contemporary Swedish grain farm growing barley, oats, spring wheat and winter wheat on 200 ha, with a conventional machinery operation chain consisting of harrowing, sowing, rolling, fertilisation, pesticide spraying and ploughing. Harvesting was not included, as the focus was on tractor-based fieldwork. The cost and environmental impacts of implements were also omitted, although the power need and working width of the implements were used as inputs in dynamic simulations of the system.

The vehicle systems studied consisted of one or more tractor, its fuel and its charging/refuelling infrastructure, including the potential for off-board energy storage. Interactions between the vehicle system and impacts from weather and soil were included in a simplified form, as were driver scheduling, breakdown rates and field-to-farm transport. The analysis focused on the vehicle system and the associated infrastructure. Further details on the scope of the analyses performed in **Papers I-V** are presented in the respective paper.

2.3 Research structure

The work performed is described in detail in **Papers I-V** and graphically explained in Figure 1. All papers explored a different facet of autonomous (self-driving) battery-electric tractors, each focusing on a different system perspective.

In **Paper I,** a model for simulating fieldwork activities on a Swedish grain farm was developed. The model is dynamic and uses a decision system based on discrete events and states. The model and its subsystems were assessed and the vehicle capacity of autonomous battery-electric tractors was analysed and compared with that of a conventional diesel tractor. Analyses were performed on the 'plug-in' conductive charging (CC) and battery-exchange (BES) charging systems for electric vehicles. Vehicle power, battery size, distance to fields and numbers of vehicles and charging stations were all varied, to find impactful technology choices and make rudimentary optimisations. Recommendations for effective vehicle systems were made and the model was further used in **Papers II-V.**

The total cost of autonomous battery-electric tractors was explored in **Paper II**. In addition to adding an economic sub-system to the model, timeliness and battery degradation were examined through separate models and their economic effects were quantified.

The possibility of local energy production and storage was explored through additional simulations in **Paper III.** A scenario with photovoltaic solar cells and battery storage on the farm was analysed and the effect of having storage for different lengths of time was assessed.

The environmental effects of the technology switch from conventional diesel tractors to autonomous battery-electric tractors were explored in **Paper IV**, where an LCA was performed. A full inventory was made and the environmental effects of production, manufacturing, use and the end-of-life (EoL) phase were analysed, choosing categories important for electric vehicles, battery research and agriculture.

Lowering the weight of tractors is a side-effect of using self-driving technology and reduces unwanted soil compaction. The effect of this on costs and environmental impacts was analysed in **Paper V**, using the models established in previous papers.

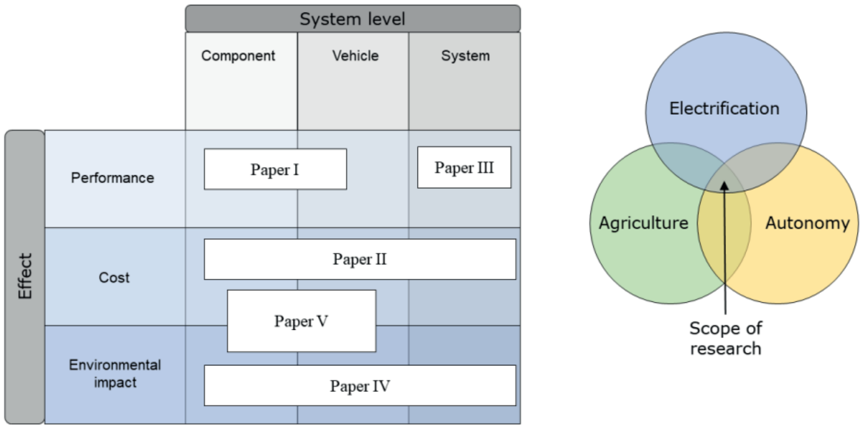

Figure 1. (Left) Graphical representation of the structure and links between research performed in this thesis. (Right) Venn diagram showing the intersection of previous fields of research, which was the scope of the thesis.

3. Background

3.1 Problem description

The past decades have seen intensification of agriculture in response to a growing global population, with the caloric supply per capita increasing by one-third since 1961 (Shukla et al., 2019). This has led to a nine-fold increase in the use of inorganic fertilisers, increasing machine weight and increased GHG emissions from the agriculture sector (Lobell et al., 2011; Shukla et al., 2019).

In order to limit human-induced global warming, GHG emissions need to be drastically reduced. The remaining carbon budget for the goal of limiting global warming at 1.5°C is 500 Gt CO_2eq, while for a limit of 2°C it is 1150 Gt CO_2eq. Annual global emissions in 2019 were an estimated 52-66 Gt CO_2eq (IPCC, 2022) and are on average still increasing year on year. Thus to stay within the carbon budget, rapid action is required. In an effort to combat climate change and mitigate its effects, the European Union (EU) has set the goal of net carbon neutrality by 2050 (European Comission, 2018). The Swedish government has set similar goals with a smaller time frame, aiming to have a fossil-free vehicle fleet by 2030 and to be net carbon neutral by 2045 (The Government of Sweden, 2013).

These goals affect machinery in the agriculture sector, where transport is heavily dependent on diesel use. In addition, agriculture in Europe and North America is facing difficulties in finding skilled labour, while also being under pressure to achieve more sustainable production and maintain economic feasibility in production (Bouge, 2016; Lowenberg-DeBoer et al., 2021). Thus there is a need for fossil-free vehicle solutions that have lower environmental impacts while providing good economic and technological feasibility.

3.2 Electric drivelines

Conventional vehicles work via thermochemical combustion of petroleum-based fuels (petrol and diesel) in an internal combustion engine (ICE) that powers the drivetrain. Electric drivelines replace the ICE with an electric power source and an electric motor. Electrification of vehicle drivelines gives advantages in emissions reduction and automotive engineering, as well as providing high torque, less need for maintenance and increased controllability (Lajunen et al., 2018). The electric motor generally has higher efficiency than the ICE because electromagnetic conversion from electricity to mechanical motion is more efficient than the equivalent thermodynamic conversion used in ICE engines, where a large proportion of fuel energy is lost as heat (Andersson, 2019). The electric motor also has fewer moving parts and makes electric transmission possible, both of which further increase driveline efficiency.

Electric motors exhibit high efficiency in their entire operating region, as shown in Figure 2. This contrasts with the ICE, which has an optimal operating region where it operates at peak efficiency of 40-50% (Chu & Majumdar, 2012). Outside this region, it quickly loses efficiency, leading to lower overall driveline efficiency, with 30% being cited for tractors (Wasilewski et al., 2017). This loss can be mitigated somewhat by using modern continuously variable gears that maximise the time spent in the optimal region, but ICEs inherently have lower overall driveline efficiency.

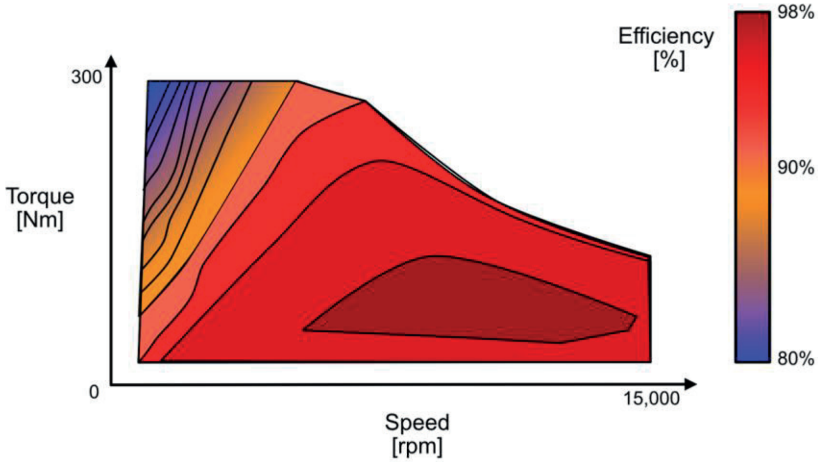

Figure 2. Simplified diagram of motor efficiency as a function of speed and torque for a warm permanent magnet synchronous motor (PMSM) designed for heavy-duty vehicles. Adapted from simulations by Andersson (2019).

Electricity is a flexible fuel that can be created locally and from low-emission sources. The Swedish average electricity mix has been shown to have a well-to-wheel climate impact of 50 g CO_2eq kWh^{-1} (Itten et al., 2014), compared with 266-321 g CO_2eq kWh^{-1} for diesel (Eriksson & Ahlgren, 2013;

Jungbluth, 2007). Fully electric drivelines have no local emissions, which is beneficial for work indoors or in emissions-free zones.

Electric vehicles can be divided into several categories, with fully electric and hybrid electric vehicles as a common subdivision. Hybrid electric vehicles utilise electricity alongside another energy source to provide propulsion, while fully electric vehicles only use electricity (Moreda et al., 2016). Hybrid solutions are a well-researched subject, both in agriculture and in general (Lajunen et al., 2018; Moreda et al., 2016; Propfe et al., 2012), and were not explored in depth in this thesis, where the focus was on battery-electric tractors.

Electric drivelines in agriculture

Agricultural tractors performing fieldwork usually operate in a single engine mode for extended periods of time and do not have a large amount of braking. In addition, long working times at high energy make high carried energy content important.

Hybrid tractors with both electric and ICE drivelines (parallel and series hybrids) have been researched, but have been found to be insufficiently profitable to take a large market share (Lajunen et al., 2018; Moreda et al., 2016). The low profitability is because the increased component costs with hybrid tractors exceed any fuel savings enabled by the regenerative braking and reduction in fuel use (Beligoj et al., 2022; Lajunen et al., 2018). Generally, hybrid vehicles are a good solution when there are frequent changes in engine speeds, where the higher efficiency of the motor can improve fuel economy, and where there is a good amount of braking, to regenerate energy (Grunditz, 2016). Neither of these is true for agricultural tractors performing fieldwork (Moreda et al., 2016).

In addition, failure to carry sufficient energy has been identified as a problem for electric agricultural vehicles, as the working time in fields can be long and any interruption in order to recharge comes at an economic cost in the form of paying driver wages for unproductive time or delaying optimal establishment of crops (Moreda et al., 2016). There have been some attempts to make electric field tractors with sufficient batteries to enable up to four hours of mixed fieldwork (John Deere, 2017) or to provide power using a direct grid connection via cable (John Deere, 2019), but neither of these drivelines has been introduced on the market. Use of electric drivelines in combination with autonomy has been pointed out as a key step in mitigating the downsides of electric machines (Lajunen et al., 2018).

Batteries

The main task of a battery is to store chemical energy and discharge it as electric energy when needed. It is therefore the enabler of battery-electric vehicles and serves the same role as the fuel tank on a conventional vehicle. Rechargeable batteries use a reversible electrochemical redox process that allows them to utilise the transformation from electric energy to chemically stored energy (charging) and that from chemically stored energy to electric energy (discharging) with high efficiency (Berg, 2015). Batteries based on lithium (especially Li-ion batteries) can achieve high energy and power densities compared with other batteries, and have therefore become the prevalent choice of rechargeable batteries in vehicles and in consumer electronics (Berg, 2015). However, they still have much lower energy-carrying capacity than liquid fuels (~0.1 kWh kg^{-1} for Li-ion batteries (Le Varlet et al., 2020) compared with ~12.5 kWh kg^{-1} for diesel (Reif & Dietsche, 2014)).

Charging stations

There are a variety of different charging systems available for electric vehicles. Two main off-board charging systems, conductive charging (CC) and a battery exchange system (BES), were studied in this thesis. A simplified diagram of these charging system is provided in Figure 3.

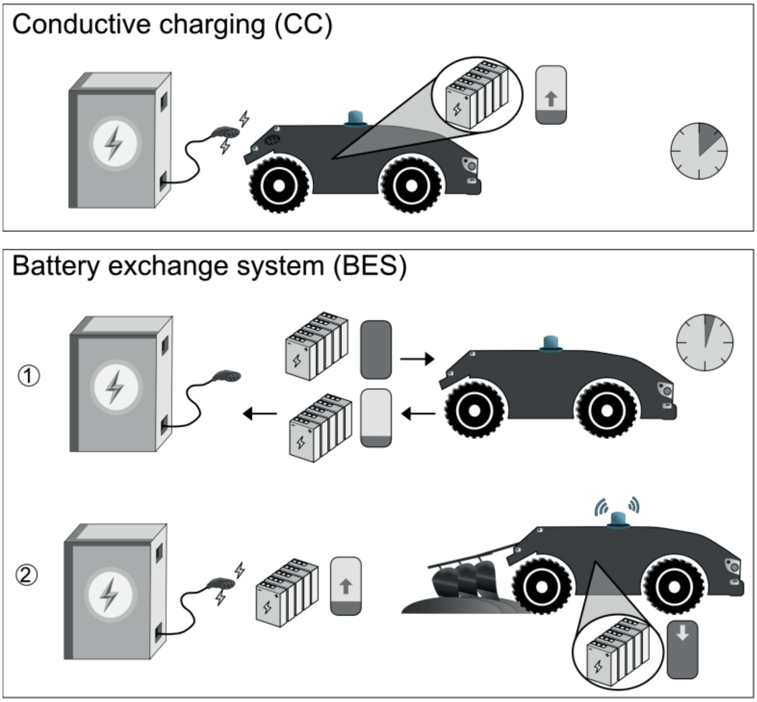

Figure 3. Graphical representation of the conductive charging (CC) system and battery exchange system (BES). Approximate time spent recharging on-site at the farm is shown in dials on the right.

Conductive charging, also known as plug-in charging, involves connecting the vehicle to the charger via a conductive plug. Power is then delivered via one of several charging methods until the battery is fully charged. The different charging methods mainly differ in how current and/or voltage is varied, and whether they use AC or DC (Yilmaz & Krein, 2013). In the CC system, charging times are dependent on the energy content of the battery being charged and the power of the charger.

The BES works by removing an empty battery pack and replacing it with a fully charged pack. The vehicle can then leave, while the empty battery pack is recharged via a CC system. Exchange times have been shown to be as low as one minute for buses and forklift trucks (Cheng et al., 2013; Song & Choi, 2015). This makes the recharging time independent of the battery energy content, which is highly advantageous for vehicles doing time-critical tasks, for example in agriculture.

3.3 Autonomy

Autonomous vehicles

Vehicle autonomy, a technology that has become prominent in the past decade, has the potential to reduce on-road fatalities and provide significant economic transformation in several sectors (Brummelen et al., 2018), (Lampridi et al., 2019). The level of autonomy in vehicles is defined on the six-point SAE/BAST scale (range 0-5) (SAE, 2021), where a fully manned vehicle without driver assistance systems is at level 0 and a fully autonomous driverless vehicle is at level 5. The levels are as follows:

- Level 0: No driving autonomy
- Level 1: Driver assistance
- Level 2: Partial driving autonomy
- Level 3: Conditional driving autonomy
- Level 4: High driving autonomy
- Level 5: Full driving autonomy

Levels 0-2 are considered to refer to manned vehicles, with varying levels of driver-assistance systems present. At this level, the driver is still legally responsible for the vehicle at all times and is expected to monitor the environment. Vehicles at levels 3-5 are considered self-driving or autonomous, and have complicated legality outside research or safe, well-enclosed areas (Svedberg, 2016). Levels 3 and 4 have a driver present, but the vehicle can operate on its own under specific circumstances (on motorways, in garages or on fields). Level 3 generally requires the driver to be ready to assume control at short notice, while level 4 vehicles can operate independently in the specified environment. Level 5 is full autonomy and requires no input from the driver/operator during operation. Vehicles at this level require no driver to be present (SAE, 2021).

Autonomous vehicles in agriculture

Driver-assistance systems are common in agriculture and parts of field work are commonly automated (GPS-steering, controlled traffic farming, headland turn assistance *etc*.) (Mousazadeh, 2013). Therefore tractors score higher on the SAE/BAST scale than on-road vehicles and are technologically closer to fully autonomous operation. Several autonomous agricultural vehicles on levels 4-5 have been proposed, from small single-task vehicles

(Fendt, 2017; Young et al., 2018) to lighter implement carriers (Bawden et al., 2014; Grimstad & From, 2017) and conventional-sized tractors (Case IH Agriculture, 2019). In addition, agricultural fieldwork contains tasks that are predictable, plannable and requiring high precision, all factors that favour autonomy. The fieldwork tasks, geometry and environment are all simpler than in complex on-road vehicle autonomy. The main stated benefits of autonomous vehicles in agriculture are labour cost savings, increased work periods, increased precision and potential for reducing soil compaction via lighter machines (Lampridi et al., 2019; Lowenberg-DeBoer et al., 2021). Autonomy also has the potential to mitigate the shortage of farm labour experienced in Europe and North America (Lowenberg-DeBoer et al., 2021), by increasing utilisation of existing manpower and replacing driver-based fieldwork with driverless work.

3.4 Systems analysis

When studying complex systems, systems analysis can be an important tool for simplifying, understanding and making decisions about such systems. It is based on the assumption that a system is more than its sum of its parts and can act differently from its components, including showing behaviours or dynamics only visible at the systems level (emergent behaviour). By thinking about the way individual components interact in a system, it is possible to gain a greater understanding than if each component were studied on its own (Gustafsson et al., 1982; Liljenström & Svedin, 2005).

3.5 Life cycle assessment

To determine the environmental impact of any process or product throughout its life cycle, LCA is a common and internationally recognised methodology that has its own ISO methodology standards (14040, 14044) (ISO, 2006). LCA includes all the process stages of a product's life cycle, from raw material acquisition to manufacturing, assembly, use and ultimately EoL (recycling, reuse or waste management). It is a commonly used tool in environmental assessment of electric vehicles, energy production and batteries (Duce et al., 2013; Loon et al., 2018; Marmiroli et al., 2018). LCA can be used to compare different processes or products in a quantitative way, or to learn about systems and the hotspots for environmental impacts. To easier facilitate comparison, each study uses one or more functional unit that is decided by the focus of the study.

The ISO standard (which was used in this thesis and related works) recognises four distinct phases of LCA: i) *Goal and scope definition*, where the purpose of the study, its system boundaries and scope are defined; ii) *inventory analysis* (LCI), which involves data gathering and modelling of the system, including its resource use, material and energy flows, to quantify its emissions related to the functional unit; iii) *impact assessment* (LCIA) where resource uses and emissions from the life cycle are translated into environmental impact and other damage categories using characterisation factors that define the contribution of each type of emission or resource to an impact category; and iv) *interpretation*, where the results from the three previous phases are collectively evaluated in order to answer the questions of the study (Duce et al., 2013; ISO, 2006).

4. Method and models

4.1 Overview

For the work presented in this thesis, different equations, models, simulations and forms of analysis were developed. This chapter presents each of these, the assumptions made during their development and the data used. Figure 4 provides an overview of model structure. The majority of the simulations were performed using the discrete-event simulation (DES) farm model. The resulting outputs were used in the economic and LCA models to determine the resulting costs and environmental impacts, respectively.

Many sub-systems, equations and calculations were used from input to results. In summary, these were:

- *Vehicle scenarios*. Choice of size and number of vehicles, fuel type and degree of autonomy. Infrastructure design (charging stations, fuel pumps, extra batteries *etc.*) were decided in this step (see section 4.2.3).
- *DES farm model (Matlab/Simulink)***.** This was used to simulate an entire growing season, including the behaviour of the tractors, energy use, weather effects and fieldwork operations (see section 4.2).
- *Energy storage model (Simulink/PVGIS).* This was used to simulate on-site storage of energy used in powering electric tractors (see section 4.5).
- *Economic model (MS Excel).* This calculated the cost of investment, operation and ownership, based on the vehicle scenario, empirical cost data and the results from the DES model (see section 4.3).
- *LCA model (SimaPro).* This analysed the environmental impact of the entire vehicle life cycle, both emissions and the resulting impacts and damage, based on vehicle scenarios, inventory data and the results from the DES model (see section 4.4)

The nomenclature presented in Figure 4 is used throughout the thesis.

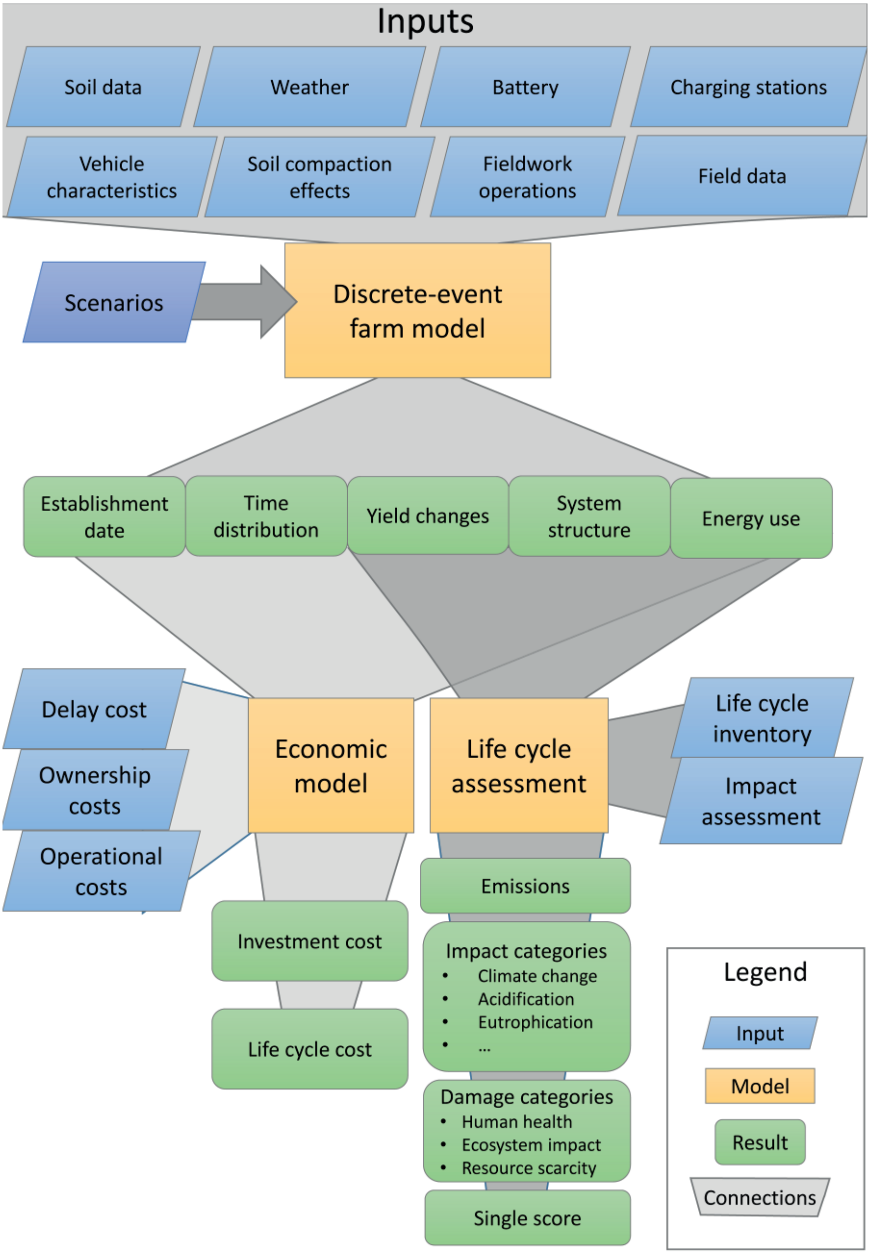

Figure 4. Overview of inputs (parallograms), models used (rectangles) and results (ovals) used, and connections between these (grey fields).

4.1.1 Model philosophy

"All models are wrong. But some are useful."
George Box (1987)[1]

In systems analysis, all models show a simplified picture of reality. They approximate the real-world system under study, as reality is too complex to model in its entirety. By choosing the key dynamics and interactions in the system, a rudimentary understanding of what is important can be gained. The researcher is responsible for deciding what is included and what is not, based on the objective of the research. Every modelling study rests on these assumptions and shows some degree of error when compared against reality. This does not mean that models are completely without value; rather, they are useful in the context for which they are created but lose usefulness outside that context.

The models created for the studies described in Papers I-V were all created with a specific context in mind. In all cases, the models were created to reflect real-world systems and the studied vehicles were then added. Note that the models were not created around the vehicles, as that would have included bias in the analysis. Instead, commonly used best-practice models and equations were used.

The concept of self-driving battery-based tractors itself has not been thoroughly studied previously, but the component parts are well understood. The aim in this thesis was to evaluate the new system obtained on combining these component parts. To overcome the lack of existing models for the entire system, several higher-degree models were created from the building blocks of existing sub-models that are generally well-researched and have been independently validated in different studies. These higher-degree models were created to show the general dynamics, in terms of different goal variables and effects, of the change in technology from single, manned diesel-fuelled tractors to multiple lighter, autonomous battery-electric tractors. Efforts were made to keep the models simple enough to be widely understood and the results to be somewhat general, but complex enough to have scientific depth and achieve an approximation of reality that was accurate enough to have wider implications beyond this thesis.

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[1]From '*Empirical Model-Building and Response Surfaces*' (1987), p. 424.

4.2 Discrete-event model

4.2.1 Model methodology

Practical field tests of a vehicle system with emerging technologies such as combined autonomous and battery-electric drivelines would be costly. In addition, since the technology is still under development and no dominant system structure has emerged, field tests would not be able to test the system at a mature stage. Since the aim of the studies in Papers I-V was to increase understanding of the potential effects of autonomous electric tractors on Swedish agriculture, simulations were employed as a practical alternative to assess the vehicles at fully realised potential. By simulating several years' worth of weather, where each year was simulated separately and weather factors were the only difference between the years, natural variations and extreme events were accounted for. Apart from the number of cycles on the batteries, no factors were carried over between years. Combining this sample size with the ability of the DES model to make decisions on specific occurrences made it possible to develop a flexible and resilient model.

In order to simulate operation of autonomous battery-electric tractors, a model was implemented in Matlab (R2022a; Mathworks, Natick, MA, USA) (**Paper I**). This model is a dynamic, deterministic model that uses DES and state-based logic for decision-making, utilising the Matlab toolboxes Simulink, StateFlow and SimEvent. In this context, deterministic means that the model has no stochastic (random) properties, while dynamic means that it describes a change over time, with the state at each time-step based on the previous step. Discrete-event simulation means that the state of the system is affected by certain events, *e.g.* in the model a tractor ('agent') can only refuel if there is a refuelling station ('resource agent') available without queue ('event').

The main agents for the discrete events were the tractors, as they were the main focus of the system, but batteries and charging stations were also agents in the simulation. A simplified flowchart of the decision tree for the control logic and different states can be seen in Figure 5.

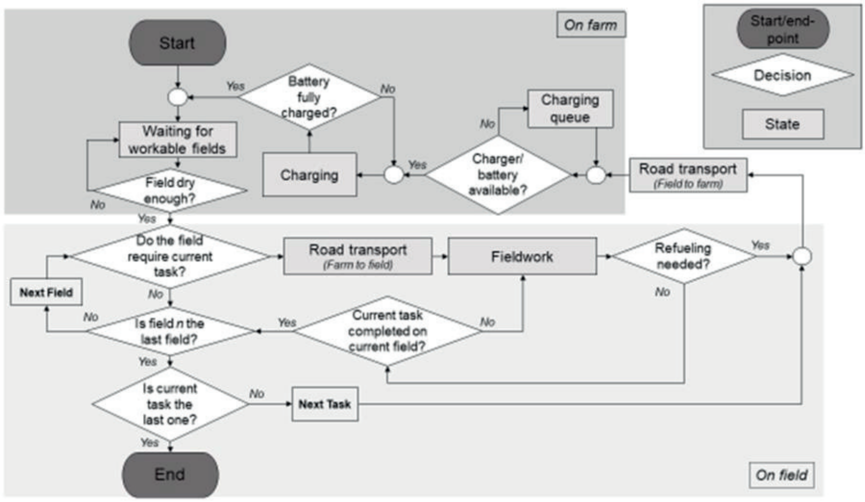

Figure 5. Simplified flowchart of the discrete-event simulation (DES) model, showing the states (grey squares) and decision points (white diamonds) for each vehicle.

4.2.2 Farm model and cropping system

In order to perform relevant analysis, a representative Swedish farm was modelled in **Paper I**. This hypothetical farm was assumed to grow grain, and barley, oats, spring and winter wheat were chosen as they are the most commonly grown cereals in Sweden (Statistics Sweden, 2018). The farm was assumed to have 200 ha of arable land, as this is the farm size for which autonomous battery-electric vehicles would be feasible, due to adequate investment capacity and machine need (Lowenberg-DeBoer et al., 2021). It is also a common arable farm size in Sweden. The arable land was assumed to be distributed as 12 fields (size 6-26 ha) at varying distance from the farm centre. These values were chosen to represent common conditions in the Uppsala region in Uppland County, central Sweden. Each crop was assumed to be equally distributed and grown on three fields totalling 50 ha. Field distribution, sizes and distances are shown in Table 1.

Table 1. *Size, distance from farm, field number and crop on the simulated fields*

Crop (*g*)	**Oats**			**Barley**			**Spring wheat**			**Winter wheat**		
Field no., *n*	1	6	8	3	4	11	5	9	12	2	7	10
Area, A_n [ha]	10	26	14	20	13	17	15	22	13	16	6	28
Distance, D_F, km	1	3	4	2	2	6	3	5	6	1	4	5

Fieldwork operations

A conventional cropping system was simulated, as the high power requirement of conventional tillage and ploughing was assumed to be a good test of the capacity of the new vehicles. Conventional cropping is also the most common method in Swedish agriculture, enabling easy comparison to other studies and field data. A no-till or no-ploughing cropping system would arguably be more fitting for the capacity of the electric vehicle system, but the choice was made to optimise the vehicles to the existing conditions, and not to change the conditions to fit the vehicles.

The growing periods and the operations used for each crop are shown in Figure 6. The operations and their order were based on Nilsson (1976), while the length of the growing season and that of each working period were based on empirical data for the Uppsala region (Myrbeck, 1998). A reserve period of one month, not included in Myrbeck (1998), was added, as ploughing can often be performed even after the dedicated autumn period.

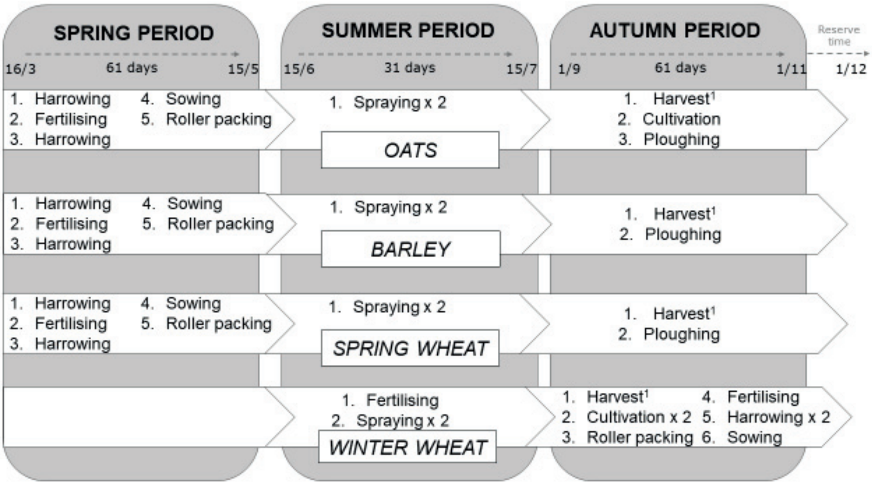

Figure 6. Working periods and crop operations for different cereal crops in the Uppsala region. [1]Harvesting was not included in the simulations, but is included in the diagram for a better representation of the order of operations.

The power requirement for fieldwork operations of both the electric and ICE tractors was taken as the sum of the power required to move the tractor and provide draught for the implement (for details, see **Paper I**). Standard equations for vehicle dynamics were used for the tractors, including rolling resistance, gradient force, acceleration force and drag force (Reif & Dietsche, 2014). The equations on the force and power requirement for the fieldwork operations were taken from ASABE standards (ASABE, 2011; ASAE, 2000), and the same equations were used for both the ICE and battery-electric tractors. The power equations optimised the working width of the implement, up to a cut-off point decided by the largest available implement of that type (as detailed in **Paper I**). Appropriate values for soil clay were used for rolling resistance, soil parameters, tillage depth and implement width. Exact values and equations are given in **Paper I**. They were used as written for **Papers I-IV**, but the power requirement was reduced in **Paper V**, as several sources have stated that the equations give roughly 15% higher values than real-world testing (Grisso et al., 2010; Safa et al., 2010).

Soil type, weather and trafficability

The geographical position of the simulated farm influenced the choice of soil type, growing season and various weather effects. The Uppsala region lies within the plains district of Svealand (Myrbeck, 1998), where soils with a high clay content (25-60%) are common (Paulsson et al., 2015) (Figure 7). Soil type affected the vehicle power requirement (presented in **Paper I**) and several factors in the soil water balance model used, as further described by Witney (1988) and Nilsson and Bernesson (2010).

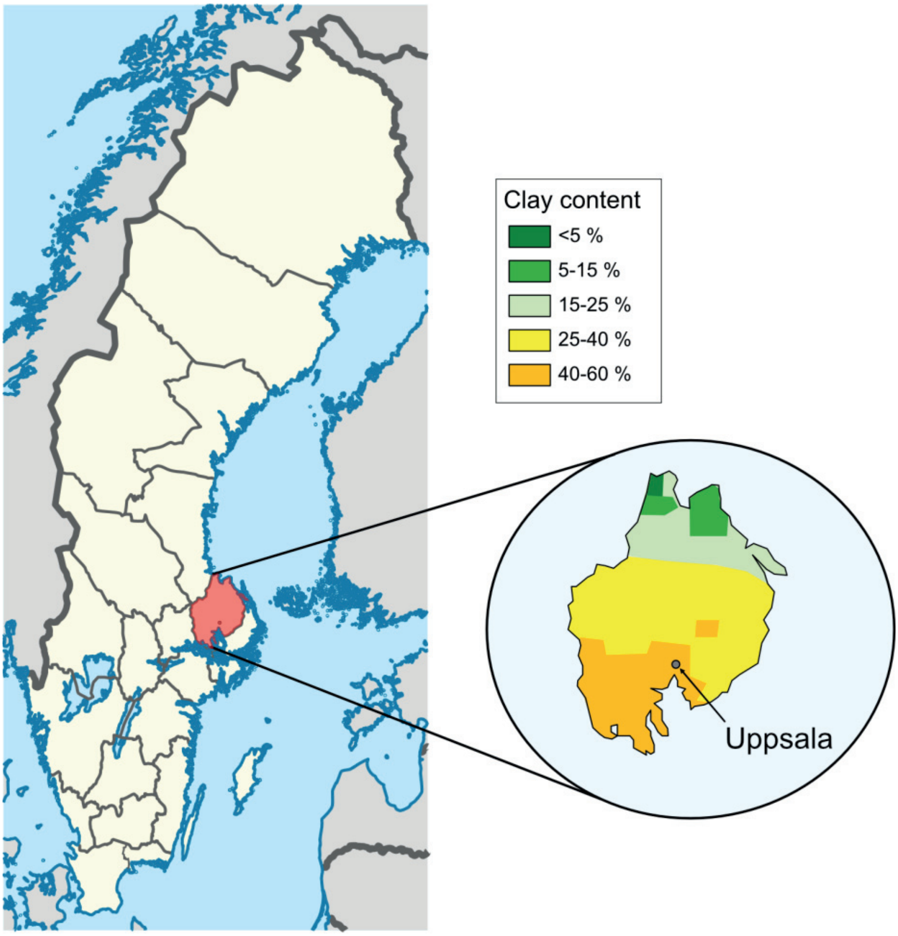

Figure 7. (Left) Map of Sweden with the study region of Uppland County around the city of Uppsala shown in red (adapted from Wikimedia Commons under CC BY-SA 3.0). (Right) Soil map of Uppland County showing clay content in the region (adapted from Paulsson et al. (2015)).

The weather effects considered were precipitation, temperature and daily number of sunshine hours, using data taken from weather stations in Uppsala, Stockholm and Enköping for the years 1989-2108 (SMHI, 2019, 2020). Multiple years of weather data were used to reduce the effect of differences between years on the results. The weather data were used as inputs for the soil water balance model, which calculated the soil moisture content for a uniform soil layer of 300 mm. The result was then compared to limits of trafficability for general tillage and ploughing, taken from de Toro and

Hansson (2004). If the soil moisture content was lower than the limit, the field was deemed dry enough for traffic, without a risk of negative soil effects (Figure 8), and the tractors were cleared to begin fieldwork. If the soil moisture level was above the threshold, the tractors waited. In **Paper I,** data for the years 1989-2018 were used. In the other studies, the number of years was reduced to lower the computational strain, as the full 30-year period was deemed unnecessary for acceptable resolution. **Papers II, III** & **V** used data for the years 2008-2018, while **Paper V** used data for 1988-2018 for simulations on hydraulic conductivity and data for 2008-2018 for machine simulations.

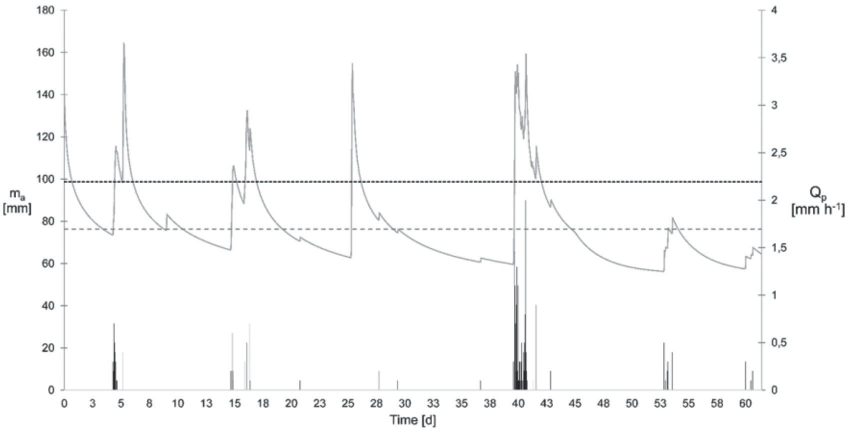

Figure 8. Example of soil moisture content in spring 2008 (m_a, solid grey line) according to the water balance model. Hourly precipitation (Q_p, right axis) is shown as black bars. Trafficability limits for general tillage (grey dashed line, bottom) and ploughing (black dashed line, top) are indicated.

4.2.3 Vehicle scenarios

Several different scenarios were simulated and compared in **Papers I, II, IV** & **V**. These were mainly vehicle scenarios with differing energy carriers (fuel/electricity), degree of autonomy, energy-carrying capacity and power (Table 2). For simplicity, they were generally divided into primary and secondary scenarios. The primary scenarios compared a conventional diesel tractor with a driver and an equivalent unmanned electric tractor system, with the aim of identifying differences between the systems, where the conventional tractor constituted the technological starting point and the electric system the technological goal. In addition, some possible variations of scenario parameters (number of vehicles, fuel, charging types *etc*.) were explored (see section 5.5) to increase understanding of the effect of technology and component choices. Sensitivity analysis on selected parameters was also performed in **Papers I, II, IV & V.**

Table 2. *Key inputs used for the conventional internal combustion engine (ICE) tractor and the battery-electric driveline (BED) tractors in the primary scenarios*

	Working time [h d^{-1}]	**No. of vehicles**	**Power (P_V) [kW]**	**Energy carried (E_B) [kWh]**	**Charger type**	**Charger power (P_C) [kW]**	**Weight (m) [kg]**
ICE	10	1	250	4,684 (463 L)	Fuel pump	30,345	10,800
BED	24	2	50	4x100	BES 2xCC[1]	50	3,527

[1]BES = battery exchange system, CC = conductive charging.

Variations in inputs such as soil compaction effects, soil type, farm-to-field distances and fieldwork operations were possible in the model, but the values were kept static to focus the analysis on the different vehicle systems.

4.2.4 Electric vehicles

The electric tractors used throughout **Papers I-V** were assumed to be general agricultural field machines with the main purpose of providing draught for fieldwork implements. A general, technology-agnostic electric motor was modelled, using variables from permanent magnet synchronous motors (PMSM) described by Andersson (2019). Motor efficiency was assumed to be a static average of 95%, with driveline efficiency (motor to wheels) of 85% (Ryu et al., 2003). The latter efficiency value was based on conventional tractors, even though increased transmission efficiency is likely for electric drivelines in heavy work machinery (Lajunen et al., 2018). The total efficiency from charger to wheels was assumed to be 74%.

Charging infrastructure

Charging infrastructure was assumed to exist at the farm centre and the tractor drove there when it needed to recharge or refuel. Recharge was either by conductive charging (CC) of permanently installed batteries in the tractor or a battery exchange system (BES) where depleted batteries were replaced by fully charged batteries in the tractor. The CC system (Yilmaz & Krein,

2013) was assumed to consist of a number (N_V) of fast chargers with a charging power variable (P_C, kW). They were assumed to recharge the batteries by a linear method, which has been shown to give an adequate fit to the constant current/constant voltage (CC/CV) recharging method often used in CC (Harighi et al., 2018; Shen et al., 2012) (Figure 9). The recharge rate was dependent on the power and efficiency of the charger and the effective energy content of the battery (E_B, kWh), as described in Equation 1:

$$\theta(t) = \theta(t_0) + \int_{t_0}^{t} \frac{P_C \eta_C}{E_B} dt;\ \theta_{\min} \leq \theta(t) \leq \theta_{\max} \quad (1)$$

where $\theta(t)$ and $\theta(t_0)$ is the state of charge at time t and when arriving at the charger (t_0), respectively, θ_{min} and θ_{max} denotes the minimum and maximum battery charge level, respectively (20% and 100% in this study), E_B is maximum battery energy content in kWh, P_C is charger power in kW and η_c is charger efficiency (95%).

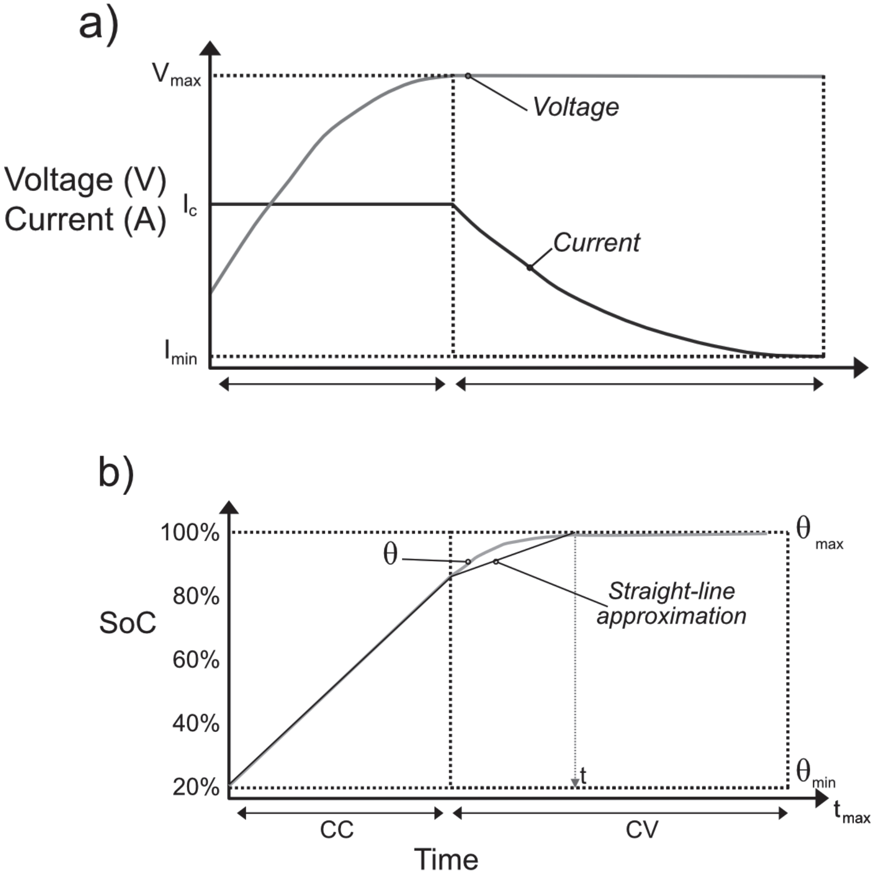

Figure 9. Simplified constant current/constant voltage (CC/CV) recharge methodology (adapted from Shen et al. (2012)). (a) Current and voltage dynamics and (b) battery state-of-charge variable (θ) and the straight-line approximation used in the model.

In the BES system, the entire depleted battery pack was replaced with a fully charged pack. The tractor could then resume operation directly after the exchange, while the depleted battery was recharged using a conductive plug-in fast charger as described above. Therefore the BES system needed both a CC system and battery exchange infrastructure. In addition, extra battery packs were required. The BES was based on existing industrial automatic transfer carriage systems (Solus Group, 2019). The exchange time was set to 10 minutes to give a margin of error, although shorter times have been demonstrated for cars (Adegbohun et al., 2019) and buses (Song & Choi, 2015).

Batteries

When modelling the battery, it first served as a general energy reservoir for the tractor, a role performed by the fuel tank in the ICE driveline. Thus the battery-electric vehicle system was kept more general than in previous studies. A Li-ion battery with nickel-cobalt-aluminium (NCA) chemistry was assumed, as it is common in electric vehicles (**Paper II**). The dynamic state-of-charge (SoC) level, $\theta(t)$, of the batteries was monitored as a single-variable way of knowing the state of energy capacity of the batteries (Grunditz & Thiringer, 2016; Tremblay et al., 2007). It describes the fraction of full charge remaining and was set to increase linearly when the battery was charged and decrease linearly when a load (commonly fieldwork or road transport) was applied, which was found to correspond adequately to the more realistic charge-discharge curves in **Paper II**. The battery had an energy variable denominating the maximum energy carried, E_B, in kWh.

A minimum SoC value, θ_{min}, was introduced at 20% to avoid damage or accelerated deterioration caused by deep discharging of the battery. In the model, the tractor was programmed to never discharge the battery under this limit.

Battery ageing

Batteries deteriorate electrochemically in two ways, through use or over time. This deterioration is mainly evident as capacity fade (reducing the energy-carrying capacity of the battery) and power fade (increasing the internal resistance and reducing power efficiency) (Uddin et al., 2016). Calendar ageing was omitted from the analysis, as one of the defining characteristics of Li-ion batteries is low capacity fade during storage (Barré et al., 2013). Instead, the focus was on capacity fade as the batteries were used frequently, which tends to lead to capacity fade being the main ageing factor, rather than time (Uddin et al., 2016).

There are several factors influencing the rate of battery deterioration, or ageing in colloquial terms, and many of these are interconnected, making clear separation of causes difficult. In this thesis, the focus was on cycle ageing, as described in Barré et al. (2013), where the batteries deteriorate over time due to charging or discharging. Charging or discharging with higher power accelerates this deterioration, so the charging rates (C-rates) were studied. The C-rate is a unit describing the rate of charge/discharge, describing how many times the battery can be fully charged in an hour. A C-rate of 1C means that the battery is fully charged in an hour, while a C-rate of 4C means the battery is fully charged in quarter of an hour (*i.e.* 15 min). C-rates of 0.5C, 1C and 4C were analysed. Due to the type of use, it was assumed that the number of cycles and the C-rate were the most influential factors (Uddin et al., 2016; Wenzl et al., 2005). Capacity fade, or ageing, can also be tracked as a battery's state of health (SoH), which tracks the fraction of the original energy-carrying capacity that remains at a given point in time.

Ageing was modelled in **Paper II** for a one-dimensional battery cell, using COMSOL Multiphysics (v5.5, COMSOL AB, Stockholm, Sweden) by S. Dhillon from Uppsala University. Modelling was based on the porous electrode theory and concentration solution theory (Thomas et al., 2002), using a graphite negative electrode, a $LiPF_6$-based electrolyte and a NCA positive electrode. A stable ambient temperature of 293 K was assumed, and a minimum SoC of 20% (or, inversely, depth-of-discharge, DoD, of 80%). It was assumed that fast charging was used in the SoC interval 20-80% and slower charging during the interval 80-100% (Figure 9), in accordance with best practice in electric vehicle charging (Berg, 2015). Where several batteries were used, such as in the BES scenario, the cycling was assumed to be distributed equally. When the capacity fade exceeded 20% of E_B (*i.e.* SoH was 80%), the battery was assumed to be replaced after the current working year, as it is a common cut-off point in the electric vehicle industry (Berg, 2015). To use the simulation results in the DES model, the capacity fade of the batteries was fitted by a third-order polynomial. These values were then used in the remaining sub-systems and models to reduce computation times. Equations, parameters and details are presented in **Paper II.**

Autonomy

The simulated tractors were assumed to be autonomous to a high degree, reaching level 4 or above on the SAE scale (sometimes known as the BAST-scale), meaning high (level 4) or full driving autonomy (level 5) (SAE, 2021). For practical purposes, this means that the vehicle was able to perform all tasks with only occasional monitoring. In the model, it was assumed that the autonomous vehicles were unmanned and self-driving and that an operator monitored their systems and status remotely.

The fraction of time monitoring that was required was described for each task by a decimal operator factor, *O,* where 0 is fully autonomous operation, and 1 is fully monitored. Previous studies have suggested values of 0.1-0.2 for all operations (Engström & Lagnelöv, 2018; Goense, 2005). Road transport was assumed to have additional complexities and was given a higher value to compensate. The operator factors used are shown in Table 3.

Table 3. *Operator factors for different tasks modelled, showing the fraction of hours in which the tractors needed to be monitored*

Task	Operator factor
Fieldwork, O_F	0.2
Road transport, O_R	0.3
Charging/refuelling, O_C	0.1
Manned operation (conventional system)	1
Waiting for drier fields	0

Although the subject of self-driving or autonomous vehicles is well-researched, no specific sensor system, components or technology were chosen for the simulations, in order to avoid producing technology-dependent results. In addition, as the scope of the study was system-scale impacts of changing to autonomous battery-electric tractors, a general autonomy system with mature technology readiness level was assumed, to better analyse the impacts of the technology in common use rather than in experimental trials. Recommendations on autonomous technology given by Mousazadeh (2013) and Hirz and Walzel (2018) were considered.

4.2.5 Conventional internal combustion engine tractor

A conventional tractor vehicle system was modelled, as it is the current system and sets the baseline for comparisons. The conventional scenario was assumed to consist of a single, manned diesel tractor with P_V of 250 kW, weighing 10,800 kg, with a fuel tank containing 463 L diesel (or 4680 kWh). Tractor weight and fuel tank size were based on modern tractor models (Valtra S294, Fendt 933 Vario, John Deere 7R330), verified with data from Mantoam et al. (2016). Manned systems were modelled to give a maximum active working time of 10 hours per day for seven days per week, partly to simplify the simulation and because this is not an uncommon work schedule in time-critical situations. A 10-hour workday was also used by Lowenberg-DeBoer et al. (2021). In practice, the actual time spent working was lower due to weather and non-trafficable fields.

The efficiency of the combustion engine was set to an average value of 30%, with total driveline efficiency of 25.5%. This corresponds to an average to high value for agricultural tractors (Wasilewski et al., 2017).

The farm centre was assumed to have a pre-existing diesel pump with a flow rate of 50 L min^{-1}, corresponding to an energy flow of 30.3 MW min^{-1}. Refuelling times were less than 10 minutes, so there was never a need for more than one fuel pump. It was assumed that the fuel pumps had perfect efficiency and no spill.

4.2.6 Soil compaction

In agricultural field operations, the weight of the vehicle plays an important role. High vehicle weight can lead to soil compaction, which can adversely affect soil health and plant growth (Bennett et al., 2019; Hamza & Anderson, 2005). To analyse the effect of the lighter vehicles possible with autonomous operation, long-term soil compaction was included in the model (**Paper V**). The assumption was that the tractors with lower weight compacted the soil in a reversible way, while the heavier machines led to long-lasting or irreversible soil compaction (Figure 10). In practice, the effect of vehicle weight on soil compaction is more gradual, but since the main comparison was between vehicle systems of very different weights, this assumption was used.

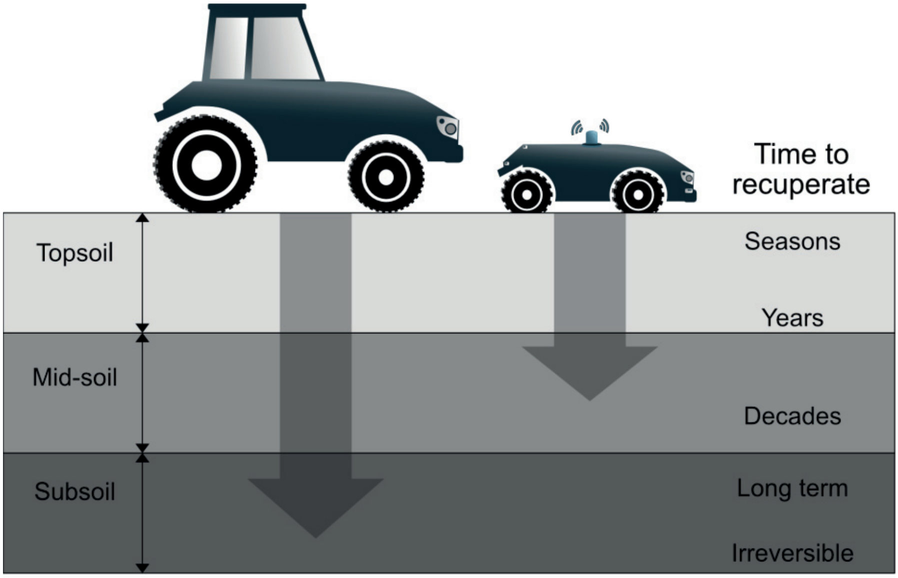

Figure 10. Simplified graphic of soil compaction impact for heavy and light vehicles.

Soil compaction is a complex field, so key changes that had large potential impacts and were likely to be affected by the change in vehicle weight were selected for analysis. These were:

1) Reduced trafficability due to a 74% reduction in soil hydraulic conductivity (Keller et al., 2017).
2) An 8% decrease in crop yield due to rooting difficulties (Keller et al., 2019).
3) Increased fuel use for seedbed preparation due to increased soil density/resistance (Keller et al., 2017). These were increased by 87%, which led to a total yearly energy increase of 29%.

These three factors are directly related to the use of vehicles and have been identified as impactful in both economic and environmental terms (Hamza & Anderson, 2005; Keller et al., 2019). The specific values are for soils with a high clay content, *i.e.* soils in the Uppsala region.

4.3 Economics

The economic model described in **Paper II** was based on total annual cost (C_{AN}), consisting of ownership costs (C_{OW}) and operating costs (C_{OP}). This was based on methods proposed by Wu et al. (2015) and Lampridi et al. (2019), with additional cost calculation of autonomous systems by Marinoudi et al. (2019) included, as well as straight-line value depreciation and the average interest rate method. Additional levels of detail were used in the calculation of battery costs, as they are an important part of the economics of electric vehicles. Several factors normally included in agricultural cost assessment were assumed to be similar for all scenarios, and were thus omitted. These included the farm itself, vehicle housing, harvest, combine harvester, insurance, inputs and seeds. The cost of the diesel pump was omitted, as it was assumed to be already present on-site, but electric infrastructure was included since the change in fuel necessitated new investment in infrastructure.

4.3.1 Investments

The investment costs of the different components are shown in Table 4, together with the assumed lifetime and the sources of data. Where possible, existing data from the agricultural or electric vehicle industry were used, while in the remaining cases assumptions were made. A general resale or salvage value of 10% of the investment cost was assumed. More details on the basis of the costs are given in **Paper II**.

Table 4. *Investment costs used to calculate cost of ownership (C_{OW}) (adapted from Paper II)*

Component	Investment cost (c)	Lifetime [y]	Source
Batteries	146 € kWh^{-1}	Varies	(Comello & Reichelstein, 2019)
Charger	50,000 €	20	(Engström & Lagnelöv, 2018; Swedish Energy Agency, 2019)
Additional chargers	25,662 €	20	(Engström & Lagnelöv, 2018; Swedish Energy Agency, 2019)
Battery changing system	10,000 €	20	(Solus Group, 2019)
Autonomy system	17,446 €	15	(Bösch et al., 2018)
Tractor, P=50 kW	45,005 €	15	(Engström & Lagnelöv, 2018; Maskinkalkylgruppen, 2020)
Tractor, P=250 kW	191,550 €	15	(Engström & Lagnelöv, 2018; Maskinkalkylgruppen, 2020)

The equations used are given in detail in **Paper II**, but followed the general form:

$$C_{OW} = \sum\left(\frac{C_x - R}{T} + \frac{(C_x - R)}{2} i_r\right) \tag{2}$$

and:

$$i_r = \frac{i+d}{1+d} \tag{3}$$

where C_{OW} is the ownership cost in €, C_x is the component cost, R is the salvage value (normally 10%) in €, T is the economic lifetime in years, i_r is the real interest rate, i is the interest rate (2.75%) and d is the inflation rate (2%).

The different operating costs were then summarised for each cost (*i.e.* fuel, timeliness *etc.*) and combined with the ownership cost to give the total annual cost:

$$C_{AN} = \sum C_{OW} + \sum C_{OP} \tag{4}$$

where C_{OP} is the operating cost and C_{AN} is the total annual cost, both in € y^{-1}.

4.3.2 Operating costs

In calculation of the operating costs, the focus was on the running costs of vehicle use, with the major contributors being fuel, maintenance and the cost of vehicle operators. The indirect cost of reduced crop yield because of delayed or sub-optimal establishment (known as 'timeliness') was also included in the operating costs. Maintenance was assumed to be reduced by 28% compared with the normal maintenance cost of an agricultural field tractor (Pettersson & Davidsson, 2009) (Table 5), as electric drivelines generally have a lower maintenance requirement than ICE drivelines (Delucchi & Lipman, 2010).

Since both electricity and diesel prices tend to vary, three-year averages (2018-2020) were used. For both, VAT was not included, as farmers are exempt from VAT. In addition, farmers are entitled to a carbon tax refund on diesel with a base level of 178 € m^{-3} (1930 SEK m^{-3}) and a proposed increase to 363 € m^{-3} (3930 SEK m^{-3}) (Swedish Ministry of Finance, 2022), which was used. This gave a price of 0.77 € L^{-1}, or 0.076 € kWh^{-1} using conversion factors from Reif and Dietsche (2014).

Table 5. *Operating costs assumed in economic calculations (adapted from Paper II, with updated energy prices from Paper V)*

Parameter	Unit cost	Source
Electricity	0.076 € kWh^{-1}	(Statistics Sweden, 2022)
Diesel	0.076 € kWh^{-1} (0.77 € l^{-1})	(Drivkraft Sverige, 2022; European Comission, 2022b)
Maintenance ICE	48.8 € ha^{-1}	(Olt et al., 2010; Pettersson & Davidsson, 2009)
Maintenance BED	35.1 € ha^{-1}	(Delucchi & Lipman, 2010; Propfe et al., 2012)
Operator	28.2 € h^{-1}	(Maskinkalkylgruppen, 2020)

ICE =internal combustion engine, BED = battery-electric driveline.

The operator cost was chosen to be a fixed hourly cost modified by the operator fraction, *O*. For example, for an hour of fieldwork (where *O*=0.2), the operator cost per vehicle would be 20% of the price shown in Table 5. In previous studies, Lowenberg-DeBoer et al. (2021) assumed a full-time employee with the possibility of extra help paid per hour, while Lampridi et al. (2019) assumed full-time oversight, but 50% lower operator cost. An hourly cost was chosen in this thesis with the intention of having high resolution for the operator costs, in order to differentiate between the scenarios in a more nuanced way and create a model with wide applicability. Moreover, prediction of the dominant future business model for autonomous vehicle management is difficult and hourly cost was an easy metric to transfer to other methods.

Timeliness

The cost resulting from non-optimal establishment or operation timing (timeliness) was included in the cost estimate (**Paper II**). It was mainly based on previous studies that characterised the loss curve as linear (Gunnarsson & Hansson, 2004)] (as done in this thesis) or parabolic [(Witney, 1988). In both those studies, sowing was shown to have a significant impact on the timeliness cost, and was chosen as the main activity to focus on. In studies of timeliness, the optimal day for establishment or machine operations is often identified, but in the model developed in this thesis it was assumed that the first trafficable day was ideal for sowing and that cost-inducing delay started from that day. The cost (S) was then assumed to depend linearly on the number of delay days (Gunnarsson & Hansson, 2004):

$$S = \sum_{n=1}^{n=12} S_n \rightarrow S_n = l_g \cdot t_n \cdot p_g \cdot A_n \tag{5}$$

where S_n is the timeliness cost in € y^{-1}, l_g is the timeliness factor in kg ha^{-1} d^{-1}, t_n is the time delay from the optimal day of sowing in days, p_g is the grain price in € kg^{-1} and A_n is the area in ha. The subscript n indicates the field number and g the type of grain.

Timeliness factors were taken from Gunnarsson (2008), yield figures were taken from a three-year (2019-2021) average of normal yields for the Uppsala region (Statistics Sweden, 2018, 2019, 2021) and grain prices were five-year (2017-2021) average aggregates from major wholesale buyers (Jordbruksverket, 2022). The values are presented in Table 6. Values for A_n can be found in Table 1 and t_n was determined through dynamic simulation.

Table 6. *Factors used to calculate timeliness costs. Adapted from Papers II & V and Gunnarsson (2008)*

Factor	Winter wheat	Spring wheat	Barley	Oats
Yield, Y_g [kg ha^{-1}]	6,809	4,557	4,847	4,321
Wholesale price]SEK kg^{-1}]	1.65	1.76	1.57	1.36
Wholesale price, p_g [€ kg^{-1}]	0.152	0.163	0.145	0.125
Timeliness factor, l_g [kg ha^{-1} d^{-1}]	55	59	40	23
Timeliness [% d^{-1}]	0.8	1.3	0.8	0.5

4.3.3 Battery costs

Batteries were considered both as an investment cost and as an operating cost, for ease of comparison. The cost of batteries over the lifetime of a vehicle depends on several factors, such as investment cost, lifetime, resale value and EoL threshold. The investment cost was set to 146 € kWh^{-1} for a NCA Li-ion battery module, including battery management system (BMS), housing and wiring (Comello & Reichelstein, 2019). Values of 113-215 € kWh^{-1} are cited in the literature and market predictions (Mauler et al., 2021; McKerracher et al., 2020; Nykvist & Nilsson, 2015; Tsiropoulos et al., 2018). The resale value was set to 10% of the starting value, although the second-life market for batteries is expanding and the actual resale value might be higher.

In order to include battery costs as an operating cost, the value had to be recalculated to either cost per cycle (€ cycle^{-1}) or cost per energy unit stored (€ kWh^{-1}), both of which are common metrics in the field. Note that the cost per energy unit stored is different from the cost per unit of energy storage capacity, even though they share the units € kWh^{-1}. The costs were calculated by using the number of charging cycles and energy use, respectively, from the DES model and dividing the battery ownership cost on these.

4.4 LCA

To quantify the environmental impact of battery-electric vehicles compared with conventional tractors, LCA was performed. The environmental impact of electric vehicles is an interesting topic that has been prolifically researched (Dolganova et al., 2020; Ellingsen et al., 2017; Hawkins et al., 2012;

Hernandez et al., 2017). Since one of the goals of this research, and of electrification of tractors in general, was to reduce the negative environmental impact by replacing diesel as a fuel, a thorough analysis of the net environmental effects was critically important.

4.4.1 Methodology

In **Paper IV**, a process-based, mainly consequential LCA was performed, including production, assembly, use and EoL in its scope (Figure 11). The methodology was based on the ISO standard (ISO, 2006), with life cycle inventory (LCI), emissions characterisation, weighing and life cycle impact assessment (LCIA) included, using methods and data from previous publications (Huijbregts et al., 2017; National Institute for Public Health and the Environment, 2016). The main functional unit was one average ha of arable land growing cereal during one year (1 ha y^{-1}). One kg of grain was chosen as a secondary functional unit for ease of comparison with other studies, as it is a very common functional unit used in LCA of food systems and agriculture (Holka et al., 2016; Roer et al., 2012; Röös et al., 2011). Both midpoint and endpoint impact categories were included, in order to obtain a broader picture of the environmental impacts of the systems, since midpoint factors are useful in measuring emissions intensity and endpoint factors measure the resulting damage in several categories (Plevin et al., 2014).

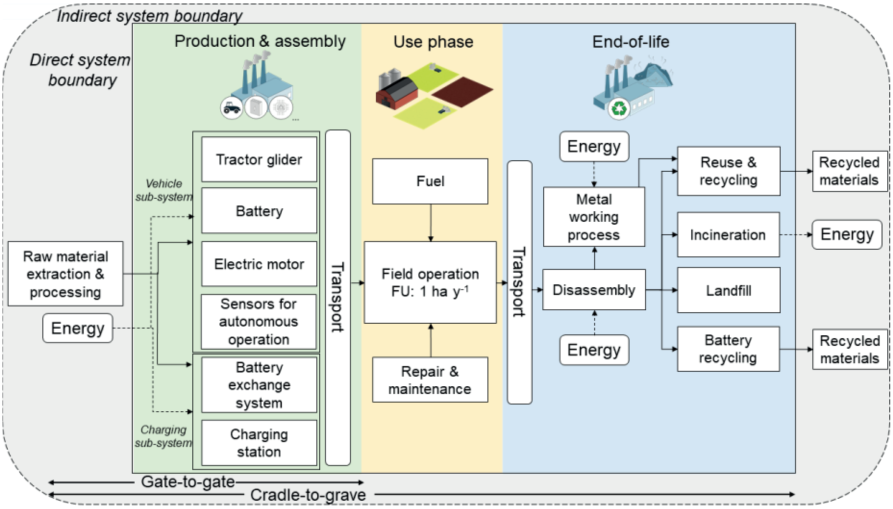

Figure 11. System boundaries applied in life cycle analysis (LCA), comprising direct system boundaries (inner rectangle) and indirect system boundaries (outer oval with dashed border). The indirect processes are not described specifically in the diagram, but were included in the results. Dashed arrows indicate energy flow.

4.4.2 Inventory

An inventory of the system (**Paper IV**) was made using the LCA software SimaPro (v9.0.0.49, PRé Sustainability, Amersfoot, Netherlands). Data from inventories of tractors and heavy-duty electric vehicles were primarily used, but components from other electric vehicles, heavy-duty vehicles and autonomous vehicles were assumed to be scalable and used in the system. The inventory is summarised in Table 7.

Table 7. *Overview of the inventory made for the vehicle systems in life cycle analysis (LCA). Components marked with * were partly included*

Phase	Category	Component	Electric	Diesel
Manufacturing & assembly	Glider (vehicle w/o driveline)	Cab		●
		Tyres and wheels	●	●
		Frame	●	●
		Chassis	●	●
	Driveline	Lead-acid battery		●
		Engine		●

		Diesel tank		●
		Transmission	●*	●
		Auxiliary fluids (oil, lubricants, AdBlue *etc.*)		●
		Li-ion battery	●	
		Electric motor	●	
	Other components	Autonomous system and sensors	●	
	Infrastructure	Electric charger	●	
		Battery exchange system	●	
Use phase	Fuel	Diesel		●
		Electricity	●	
	Repair and maintenance	Repair	●	●
		Maintenance	●*	●
End-of-life	Disposal	Vehicle disposal	●	●
		Infrastructure disposal	●	
	Recycling	Battery recycling	●	

Manufacturing and assembly

Two different main scenarios were assumed in this thesis, with several possible variations. These scenarios were: i) a contemporary ICE system with a single diesel tractor of 250 kW weighing 10,800 kg, and ii) two autonomous, battery-electric tractors with assumed unloaded weight of 2527 kg, exchangeable NCA Li-ion batteries of 100 kWh and power of 50 kW through a PMSM motor (Nordelöf et al., 2017), all which needed to be manufactured. The materials used for repair and maintenance were modelled as extra tractor components in the manufacturing process. The manufacturing of necessary infrastructure for battery recharging and exchange was also included in the inventory, as was their installation on-site.

Use phase

In the use phase the focus was on fuel use, which has been proven to be a major contributor to the environmental impact of heavy-duty vehicles (Mantoam et al., 2016). Data on fuel use by the battery-electric tractors were taken from the dynamic DES over the vehicle lifetime of 15 years. For the ICE, a dataset based on emissions from combusting diesel in agricultural machinery was used, as it was a good fit for the system described (Jungbluth, 2007). For electricity, Swedish marginal mix, consisting of 41.4% imported electricity from natural gas, 35.1% wind power and 23.5% produced from woody biomass (Itten et al., 2014), was assumed. This was validated with more recent electricity mix data (Swedish Environmental Protection Agency, 2020). For both scenarios, repair and maintenance data followed guidelines for agricultural machinery, with the exception that engine oil, AdBlue and some lubricants were omitted for the electric vehicle scenario, where they are not used (Mantoam et al., 2016; Nemecek & Kägi, 2007). The batteries were considered in the use phase, as they were replaced when they reached SoH of 0.8. Depending on the C-rate, this gave the batteries different lifetimes, with the main scenario having a service life of 15.5 years and a cycle life of 7760 cycles (**Paper II**).

End-of-life

The EoL stage was modelled in line with a method following guidelines for electric vehicles (Loon et al., 2018; Siret et al., 2018) and agricultural machinery (Nemecek & Kägi, 2007). Disposal of the ICE tractor was included in the dataset used (Nemecek & Kägi, 2007), so the disposal described here is for the electric vehicle driveline. Battery disposal is an uncertain process that is reported to need extra care when larger batteries are used (Loon et al., 2018; Siret et al., 2018), so it was given an additional level of detail. In this thesis, the method proposed by Siret *et al.* (Siret et al., 2018) was used. Generally, the components of the tractor could be recycled, incinerated for energy recovery, incinerated as hazardous waste management or sent to landfill. The material in metal parts was assumed to be recycled to 100% after an additional metal-working process, while rubber, plastics and paper were assumed to be incinerated for energy. Concrete and glass were assumed to be sent to landfill. Additional disassembly and shredding of the vehicles were required for some disposal, and all disposal types were assumed to be performed within Sweden, for logistics reasons. The disposal pathway for each component is described in detail in **Paper IV**.

4.4.3 Life cycle impact assessment (LCIA)

Impact assessment categories were taken from the ReCiPe method and the SimaPro software (National Institute for Public Health and the Environment, 2016; PRé Sustainability, 2020). Eighteen impact categories are available and all 18 were used to calculate damage categories and the weighted score (Figure 12). The most frequently used impact categories from LCAs on electric vehicles, batteries and agricultural machinery were compared to the 18 available and 11 were chosen to be presented, based on frequency (**Paper IV)**. This was done to encompass the vital emissions and impacts within the scope of all sectors described, since agriculture and electric vehicles represent different areas of study in environmental analysis.

The emissions in the respective midpoint impact categories were then weighed to get an endpoint damage impact in three categories: human health, ecosystem impact and resource scarcity. Human health was measured in disability-adjusted life years (DALY), where each unit represents the equivalent loss of one year of life. Ecosystem impacts were measured as number of species lost over a set period (species y), while resource scarcity was measured as cost increase of future resource production ($US\$_{2013}$) (PRé Sustainability, 2020). The conversion factor to go from midpoint to endpoint impact category depends on the perspective chosen. In this thesis the ReCiPe hierarchist perspective was chosen, as it is the default perspective and offers a good balance between short and long-term scopes (National Institute for Public Health and the Environment, 2016). The conversion from emissions to impacts is shown in Figure 12. The conversion factors can be found in **Paper IV.**

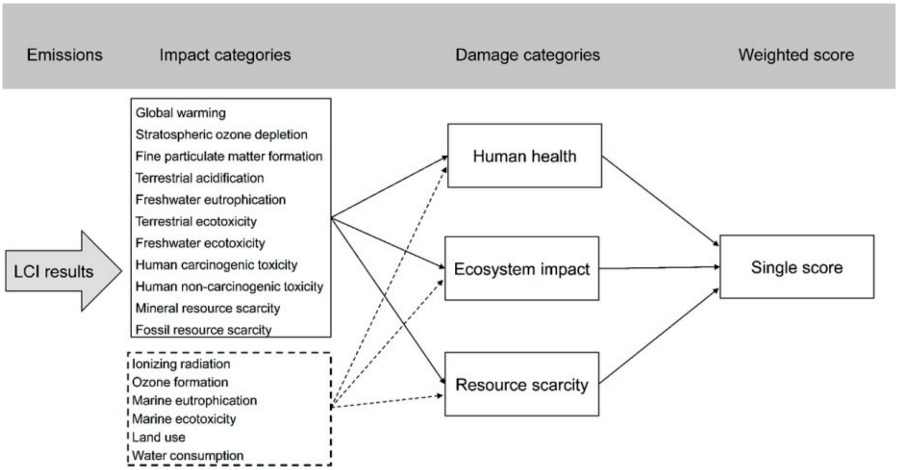

Figure 12. Framework for the life cycle impact assessment (LCIA) used in Papers IV & V, with all impact categories shown, divided between the fully represented (solid rectangles) and indirectly included (dashed rectangles).

4.5 Local energy production & storage

Simulation of local energy photovoltaic (PV) production and storage in combination with the electric tractors was performed in **Paper III**. The model used in simulation consisted of three main components: a power source (PV solar cells), stationary energy storage (Li-ion batteries) and a power sink (charging station for the electric tractor). A simplified system overview can be seen in Figure 13. The aim was to investigate the relationship between storage and production on-site, in order to identify suitable storage periods that might reduce costs.

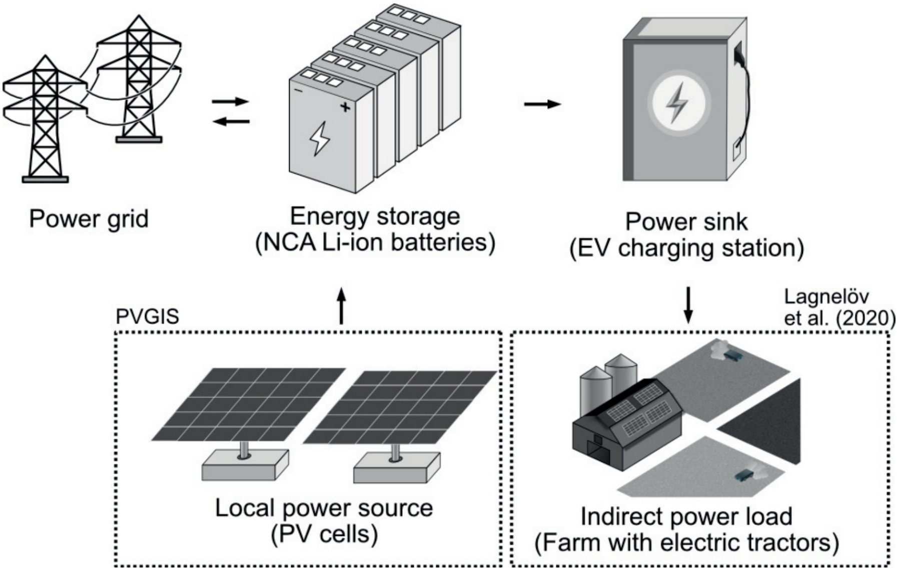

Figure 13. Simplified system structure with system components and power flow (black arrows) used in simulation of local energy photovoltaic (PV) production and storage. Complementary models used are shown with dotted squares. EV = electric vehicle.

Production was estimated using PVGIS (European Comission, 2022a) for four different solar cell mountings that each had their configurations (slope and azimuth) optimised in PVGIS. Production was set to equal the yearly power requirement of the electric tractors, so that with infinite storage potential, no additional energy would need to be purchased. The system always delivered electricity to the tractors on need, so if the energy storage was empty the electricity was purchased from the power grid. The energy storage size was the main variable investigated, and the value was varied. The storage was simulated for three types of period: between night and day, between trafficable field conditions and between seasons.

5. Results and discussion

5.1 Driveline comparison

5.1.1 Technology pathways and system structures

In order to create an autonomous electric-battery tractor system that was comparable to a conventional diesel tractor, the simulations were run iteratively to find a system structure and adequate values for the simulation inputs and parameters. Several different alternatives in technological development were simulated, to assess the changes caused by individual parameters to the studied metrics and how these changes were connected. By iterating system structures and studying the effects on performance, costs and environmental impact, a system with good performance in all metrics was identified. The steps visited along the way showcased the general dynamics involved in the different choices of system structure. The following paragraphs briefly describe how the system structure was changed in Papers I-V.

In **Paper I**, performance comparisons were made between a conventional diesel tractor, autonomous electric tractors with CC or BES charging and an autonomous system with two 50 kW diesel tractors. The results showed that autonomy was required for the electric systems to have comparable performance (tracked as active vehicle time) to the conventional systems. The electric systems achieved lower duration in-field and a resulting increase in transport between farm and field. The time spent on recharging was also higher, both because of the higher frequency of recharge required and because recharging was slower than refuelling. The diesel tractor refuelled ~250 times per year, with each refuelling event taking 2-3 minutes, while the electric tractors recharged 500-1250 times per year, with each recharge event taking 10 minutes for the BES and 1-2 hours for the CC system. The electric chargers had power of 50 kW, while the fuel pump had power corresponding to 30,300 kW (50 L min^{-1}). To reduce the charging time, BES was chosen as the standard charging technology in subsequent studies, as it was able to reduce the recharging time by up to 90% compared with a CC system and was therefore better suited for time-sensitive situations.

An evaluation of different sizes and numbers of batteries, charging stations and tractors was performed in **Paper I**, as a nominal range sensitivity analysis (changing one parameter at a time). The results indicated that an increase in individual parameters did not have a large impact on the performance, but instead that it was important to find and eliminate bottlenecks. An increase in battery size or in number of vehicles without increasing the charging capacity led to less transport time, but longer recharge times. Increased vehicle power without increasing battery size led to a higher work rate, but more frequent recharging. Thus a balanced system that sought to minimise unproductive time (mainly transport and charging) gave the best performance results. A system of two autonomous electric 50 kW tractors with 50 kWh batteries and BES charging met these criteria and was used in subsequent studies. The analysis also showed that electrification of conventional systems provided too low a work rate, but that autonomy without electrification was a plausible pathway, as it provided an increase in performance over the manned system.

Economic performance and battery management were further explored in **Paper II**, where a scenario analysis of different systems was performed. Unlike in **Paper I**, several parameters were varied for each scenario. It was found that ensuring long battery lifetime and usage through good battery management was highly economical. Therefore the original battery size was increased from 50 kWh to 100 kWh and the number of chargers was increased to two. This led to a lower charging rate (C-rate) and a reduced number of yearly charge/recharge cycles, leading to longer battery life and lower battery costs over the lifetime. The results for different secondary scenarios investigated showed that a small on-board battery (25 kWh) with several exchange batteries was a poor replacement for a system with larger on-board batteries but fewer available for exchange, as the time spent in-field became too short to be functional, while also ageing the batteries quickly and requiring frequent replacements. It was also shown that partial autonomy (18 h d^{-1}) was economically comparable to a conventional diesel system, while full (24 h d^{-1}) autonomy showed better economic and work rate performance than the conventional system.

Paper IV confirmed the findings in **Paper II** in terms of system structure, showing that even when large (100 kWh) battery packs were used, the environmental impact was lower than for the conventional system, where fuel use had a major impact. To reduce unproductive time and ensure that the system had the necessary capacity, two extra batteries (making a total of four 100 kWh batteries) and two fast chargers were assumed. **Paper V**

related the system structure to the weight of the vehicle and showed that heavier vehicles had negative consequences in the form of soil compaction.

The assumed final system structure was two fully autonomous 50 kW tractors with exchangeable 100 kWh NCA batteries, with each vehicle having one extra battery for quick replacement at a BES location. Two 50 kW CC/CV chargers were assumed to be available at the same location to charge the empty batteries. These chargers also each had a 3 kW charger for ‘slow’ charging during the off-season, in periods of bad weather or for maintenance charging. Each tractor weighed 2527 kg unloaded and 3527 kg with a battery pack on-board.

5.2 Time and delays

5.2.1 Time distribution and fieldwork operations

The main consequence of the vehicle shift explored in **Paper I** was a change in performance. A change to autonomous electric vehicles led to both a change in the total time taken for different fieldwork operations and a change in the distribution of time (Figure 14). The inclusion of autonomy removed the requirement for driver rest, while electrification of the driveline gave a triple effect. The first effect was that a reduction in the amount of energy carried (from 4684 kWh in diesel tank to 100 kWh in a battery) reduced the duration of each fieldwork stay before recharging was required. This can be seen in the increased fraction of time spent in transit between farm and field (Figure 14). The second effect was more efficient energy use for the electric driveline (see section 5.2.2). The third effect was increased time spent replacing the battery or queueing for a fully charged battery. The time spent waiting for better weather was independent of other factors and was similar for both the conventional and autonomous electric vehicle scenarios. It is worth noting that even though the fraction of time spent on fieldwork differed, the absolute active time spent was similar (18-19 days’ worth of active time). The sum of yearly active time was 97 days for the manned diesel tractor and 70 days for the autonomous electric tractors, with most of the reduction being explained by autonomy.

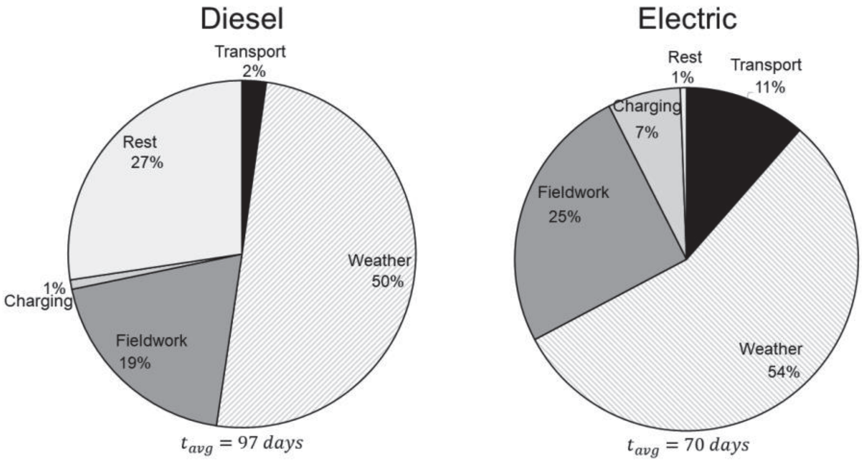

Figure 14. Time distribution, as fraction of total time, for (left) the conventional diesel tractor scenario and (right) the autonomous battery-electric tractor scenario, with the sum of active time shown under each chart. Values shown are averages for 11 consecutive years with differing weather (2008-2018).

An effect of the reduction in rated vehicle power was inability to use implements of the same size as in the conventional scenario. The model handled this by calculating the power required to move the tractor and then sizing the implement so that the remaining power was used on the implement, up to a maximum implement size taken from empirical sources (**Paper I**). The resulting working width, and consequently the rate of work, is shown in Figure 15. This assumption explains why the diesel tractor seemed to have spare power for some operations compared with the electric tractors (Figure 16).

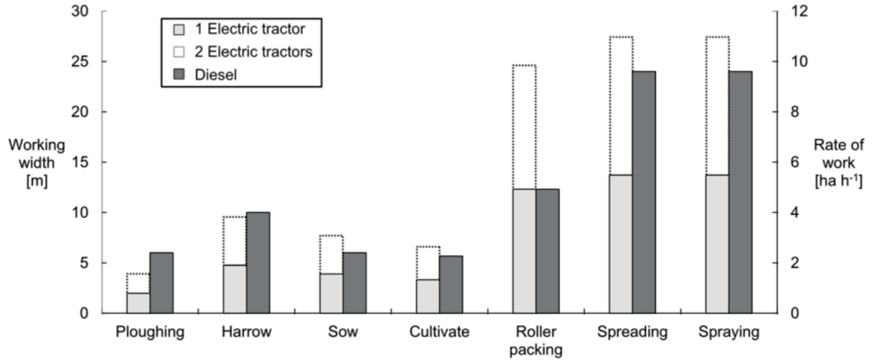

Figure 15. Working width and average rate of work (C_O) of the electric and diesel tractors in different fieldwork operations. For the electric tractor scenario, the rates with both one and two tractors are shown.

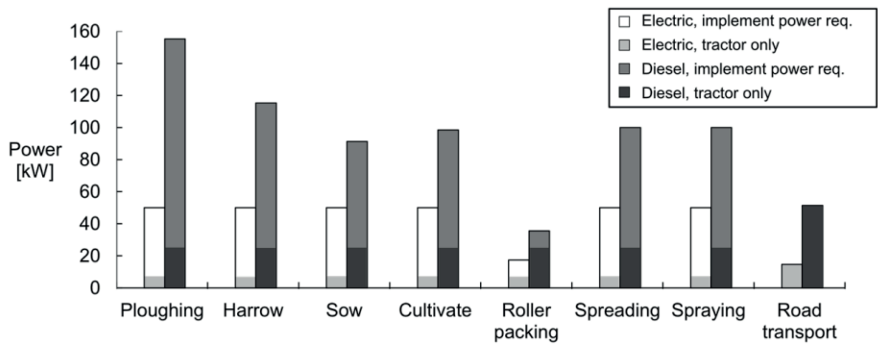

Figure 16. Average power requirement for fieldwork and average road transport in the primary electric and diesel tractor scenarios.

It is worth noting that the rate of work shown is per hour and that the autonomous electric system had the potential for more active hours than the conventional system, and therefore likely a higher rate of work on a daily basis than shown in Figure 16. In any case, the rate of work for the system with two electric tractors was comparable to that of the conventional diesel tractor system on an hourly basis.

To evaluate the difference brought about by increased fieldwork speed, simulations were run with differing in-field average speeds for the conventional tractor, up to 10 km/h (Figure 17). Higher average speeds were not tested in previous studies or included in standards (Kitani et al., 1999; Lindgren et al., 2002; Witney, 1988). It can be seen from Figure 17 that the required time approached a value similar to that of the autonomous electric tractors at t_{avg}=70 days, and a similar cost of timeliness for both cases at 9-10 km/h can be assumed. The rate of improvement decreased with higher vehicle speeds, indicating diminishing returns on higher vehicle speeds.

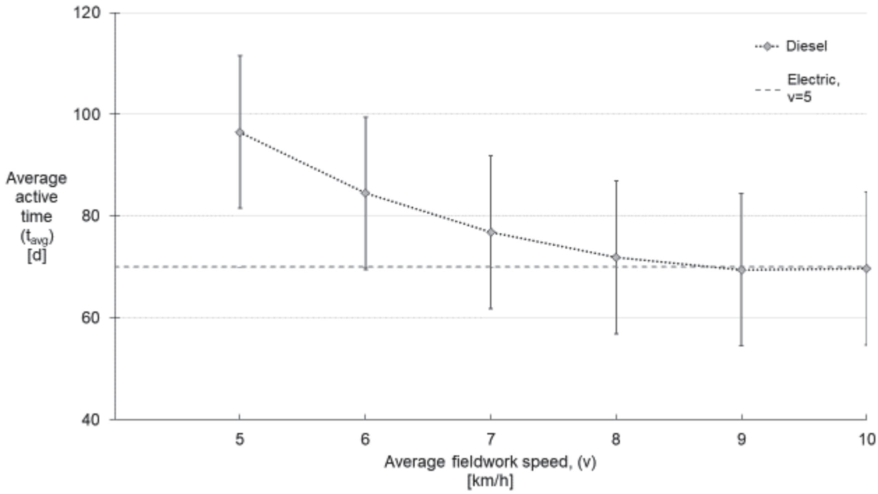

Figure 17. Average active time (simulated) for the conventional internal combustion engine (ICE) tractor as a function of vehicle speed in-field. The simulation was run for 11 separate years for each speed. Error bars show +/- 1 SD.

The completion dates for different fieldwork operations also differed between the scenarios, with the electric tractor scenario able to complete operations at an earlier date than the conventional scenario (Figure 18). The time-critical spring operations were completed in 35 days, compared with 48 days for the conventional system. Compared with the dates given by Myrbeck (1998) for timely establishment and sowing, both systems were within the normal range and completed work earlier than the average date for central Sweden (5/5), indicating adequate machine capacity by Swedish standards. A comparable rate of work to the conventional system and an increased number of workable hours per day for the autonomous electric system allowed it to complete the fieldwork tasks at an earlier date than the conventional system.

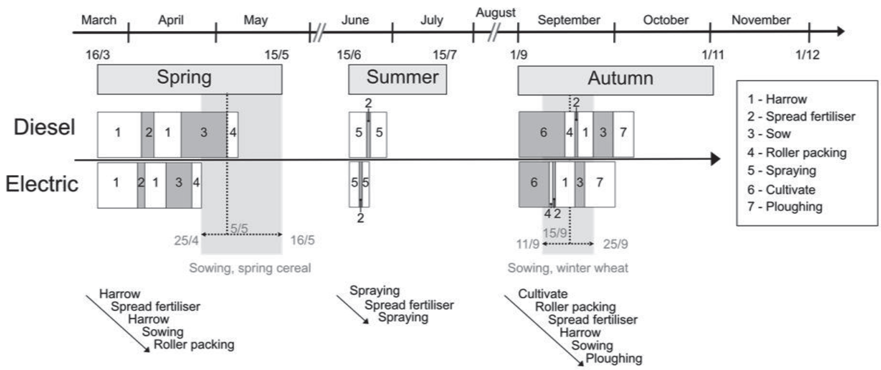

Figure 18. Order of fieldwork operations and date of completion, with the date for working periods (spring summer, autumn) and sowing recommendations by Myrbeck (1998) also shown (light grey fields). Black dotted arrows indicate the range of recommended sowing dates and the average sowing date for central Sweden is shown as a black dotted line.

5.2.2 Impact of electrification

Energy use

Electrification of the vehicle driveline led to increased driveline efficiency, as shown in Figure 19, and an associated reduction in energy use, resulting in total efficiency of 74%, compared with 26% for the conventional system.

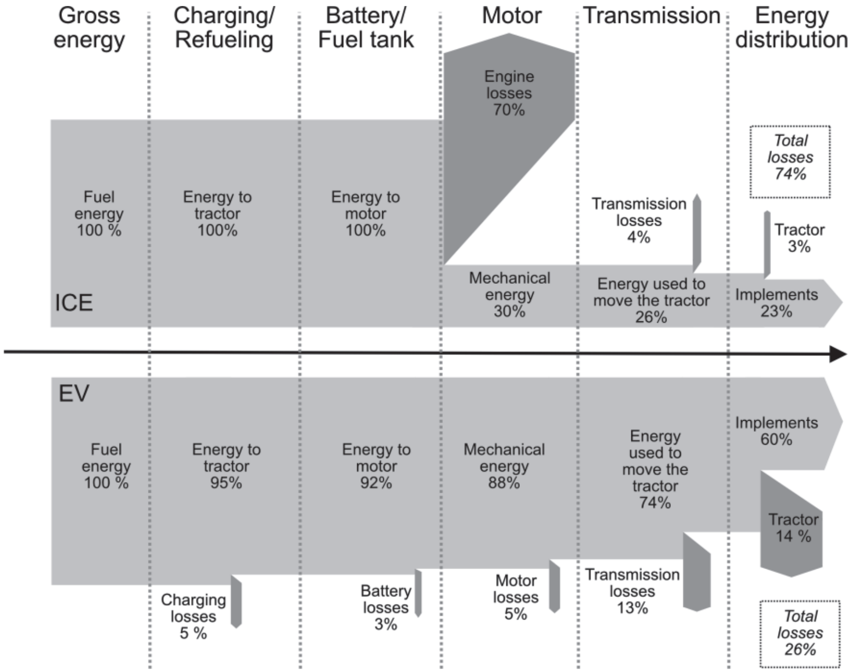

Figure 19. Cascade graph of driveline and vehicle efficiencies in each main step for the internal combustion engine (ICE) and autonomous electric vehicle (EV) scenarios, with losses and final available energy distribution. Energy distribution describes the ratio between energy used to move the tractor and energy available for implement draught. Note that transmission was η=0.85 in both cases.

The energy use in the different scenarios came to a yearly average of 58,500 kWh y^{-1} for the electric system and 153,800-230,600 kWh y^{-1} (76-113 l ha^{-1}) for the diesel tractor (Figure 20), with the range of values depending on whether additional fuel use caused by soil compaction (**Paper V**) was included or not. For comparison, data obtained in a field test on conventional tillage in the Uppsala region under similar conditions as those simulated, when converted to the same operation order and frequency used in the model, indicated energy use of 107,600 kWh y^{-1} when omitting further soil compaction and 152,000 kWh y^{-1} when it was included (53 and 75 L diesel ha^{-1}, respectively). This resulted in an energy use reduction of 47-75% when transitioning from the conventional diesel vehicle system to the autonomous electric system. These results are in line with literature results, albeit slightly higher.

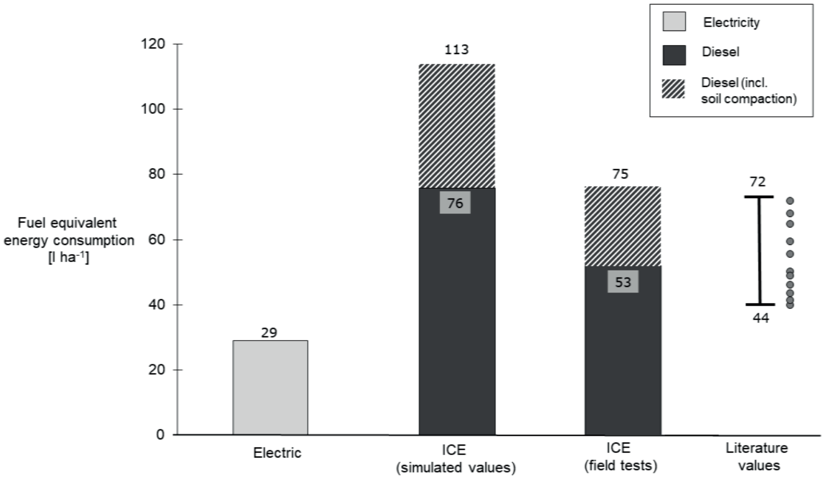

Figure 20. Energy use in the internal combustion engine (ICE) and electric vehicle scenarios, with the simulated values shown in comparison to field test values (Lindgren et al., 2002) and literature values (interval and grey dots, (Baky et al., 2010; Daalgard et al., 2001; Grisso et al., 2010; Safa et al., 2010; Wells, 2001; Witney, 1988)). Note that the literature values do not include roller packing or road transport. Harvesting was omitted in all cases.

Battery results

Battery management was found to be important for the electric tractors (**Paper II**). As the charging rate and cycles were determined to have the greatest effect, the resulting simulation showed the different cut-off points at which batteries should be replaced for different C-rates and cycle numbers (Figure 21). The cut-off point was set at SoH = 0.8, which for C/10 occurred at 7760 cycles, for 1C at 4240 cycles and for 4C at 1200 cycles (**Paper II**). The number of batteries and recharging frequencies affected the number of years that elapsed before this number of cycles was reached. Systems with more batteries spread the cycles evenly and large batteries required fewer recharges per year. This led to systems with many and/or large batteries having the best cycle life.

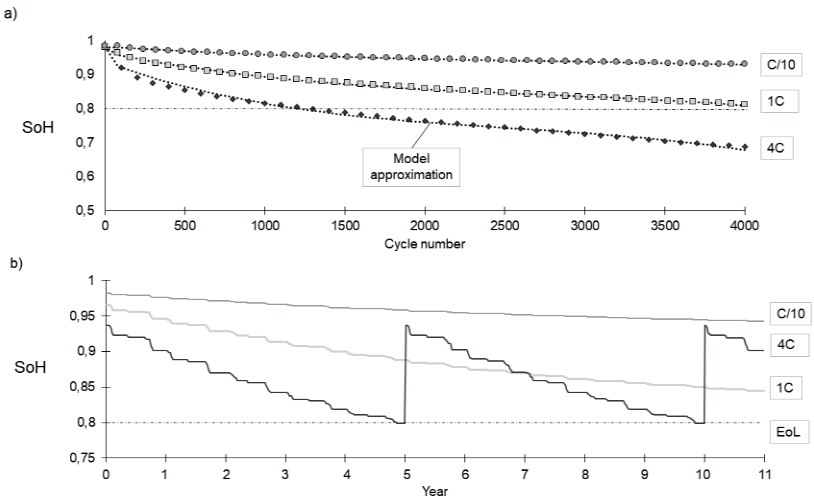

Figure 21. Battery ageing simulation of state-of-health (SoH) with increasing number of cycles and (b) increasing number of years at different charging (C)-rates (4C, 1C, C/10. End-of-life (EoL) is indicated at SoH = 0.8 (horizontal dotted line) and curve-fitting approximation used in simulations is shown in (a). The replacement frequency shown in (b) was simulated for the primary autonomous electric tractor scenario.

A commonly cited solution to the low energy-carrying capacity of batteries compared with a tank of diesel is to use larger batteries. This parameter change was tested and found not to yield the expected results. Since increasing the energy-carrying content of the batteries (E_B) increased both the time the tractor could work in-field and the time it took to recharge a battery with conductive charging, these effects almost cancelled each other out. This meant that there was only a small performance increase on doubling E_B from 50 to 100 kWh without any other changes. What was gained in work time was lost in charge time, as can be seen in Figure 22, so increased battery size only gave minor net benefits.

It was found in **Paper I** that other changes were required when changing the battery size, depending on the charging system. When the CC system was chosen, an increase in battery size also needed an increase in charger power to keep the charging time low and not create queues. Alternatively, BES could be adopted if there was an adequate number of batteries available, and then the charging power could be lowered. The number of batteries available would ideally allow the tractors to always receive a full battery when they returned for recharging. With the 100 kWh batteries and 50 kW CC chargers assumed in this thesis, there were equal numbers of chargers and tractors and each tractor had one extra battery, making a total of two per tractor.

A similar effect was found for increases in vehicle power (P_V), as increased useful power led to an increase in working speed, but also faster discharging of the batteries, which in turn led to more frequent recharging. This can be seen in Figure 22, where doubling the vehicle power led to only a minor decrease in the time required for field operations. In order to gain the full benefit, increased battery size was also required, which in turn necessitated an increase in charging potential. Thus, no single parameter was key to higher system productivity and the system as a whole needed to be optimised, as almost all parameters showed a similar trend of diminishing returns (Figure 22).

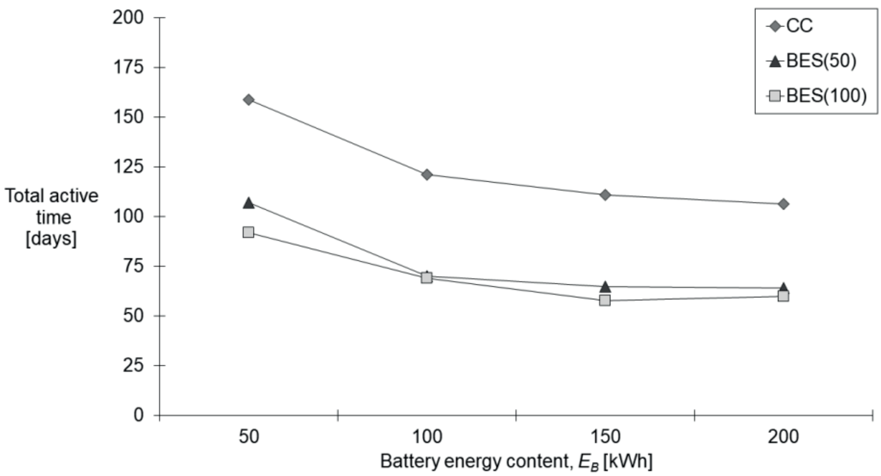

Figure 22. Active time requirement for fieldwork as a function of battery energy content for conductive charging (CC) and two cases of battery exchange systems (BES). All cases showed a diminishing return from only increasing a single parameter.

5.2.3 Energy storage simulations

It was shown in **Paper III** that production of PV solar cells did not match the energy requirement of the autonomous electric tractors. They worked whenever the fields were trafficable, which spread the distribution of charging times across 24-h periods, while the solar cells produced electricity only during daytime, so storage was deemed necessary to benefit from local solar energy production. There was also a mismatch in seasons, as the solar cells produced more energy in the summer, when demand by the electric tractors was low, than in early spring (March-April) or early autumn (September-October) when the demand was highest (Figure 23).

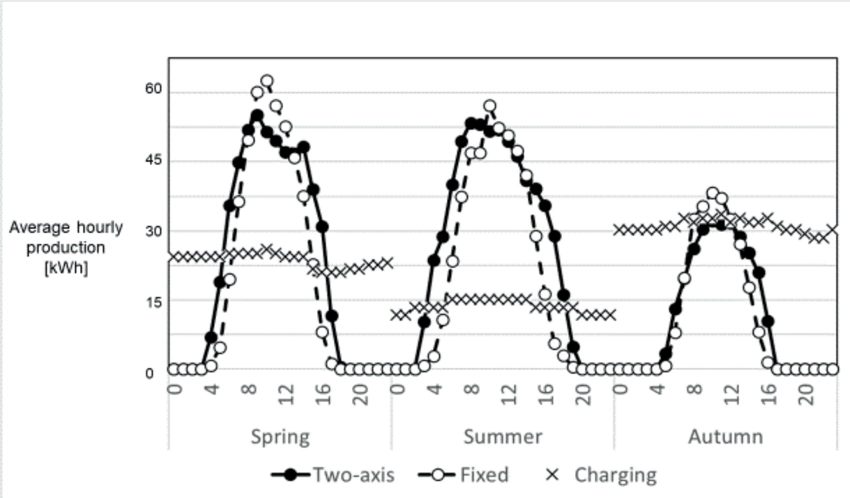

Figure 23. Average solar energy production levels (o, ●) and demand (xxx) as a function of hour of the day during spring, summer and autumn. 'Two-axis' and 'fixed' refer to different solar cell configurations.

The simulation results obtained in **Paper III** showed that the storage batteries needed to be at least as large as the batteries on the tractor in order to be useful. The batteries had three states, full, empty and active, with active being the state when the battery had energy to discharge but could also store more, *i.e.* it was the most useful state. Batteries with storage capacity of under 50 kWh acted in a binary manner, either being empty (if a charging event had recently happened) or full, with no active time between. Batteries that could store more than 10 hours of production were able to store all electricity produced from day to night, while batteries that could store 100-300 hours were able to store energy between periods with workable conditions. Storage between seasons required very large batteries and was found to be unfeasible.

With the electric and battery costs assumed in **Paper III**, there was no economic benefit in local production and storage based solely on use by the electric tractors. Even though the production cost was low, the cost of buying sufficiently large batteries to ensure a high degree of availability proved to be excessive. It is possible that with decreasing battery prices, increased electricity prices and more on-farm uses than for tractor energy, the system could become profitable. The storage battery was available for alternative uses for 76% of the year, so the profitability of the system would be highly dependent on alternative uses.

5.3 Economic impact

5.3.1 Investment costs

The investment costs of the different scenarios varied in terms of where the main costs arose (**Paper II**). In the conventional system, one of the few capital investments was in the tractor itself (in addition to implements and combine harvester, which were omitted), which had a purchase cost of 191,600 € with an additional 4,000 € in capital costs (interest rate and inflation over the vehicle lifetime), giving a total of 195,600 € (Figure 24).

The investments needed for the autonomous electric tractor were more varied, but generally comprised machine costs and infrastructure. It was assumed that the electric charging infrastructure (charging station establishment, additional fast chargers and battery exchange systems) needed to be established on-site, at a total cost of 85,700 €. Each electric tractor had a purchase cost of 71,200 €, which included the electric driveline, autonomous system and two 100 kWh batteries. Each battery had a cost of 14,600 €, giving a total battery cost of 58,400 € for the system. The battery could also be characterised as an operating cost, of 7.5 € $cycle^{-1}$ or 0.067 € kWh^{-1}.

The total investment cost for the electric scenario was 262,600 €, of which 177,000 € was machine costs. This is comparable to the machine costs for the conventional scenario, although the total investment cost was higher for the electric tractors. This is in line with results from other sources, where electric vehicles often have a higher investment cost than their conventional counterparts (Wu et al., 2015).

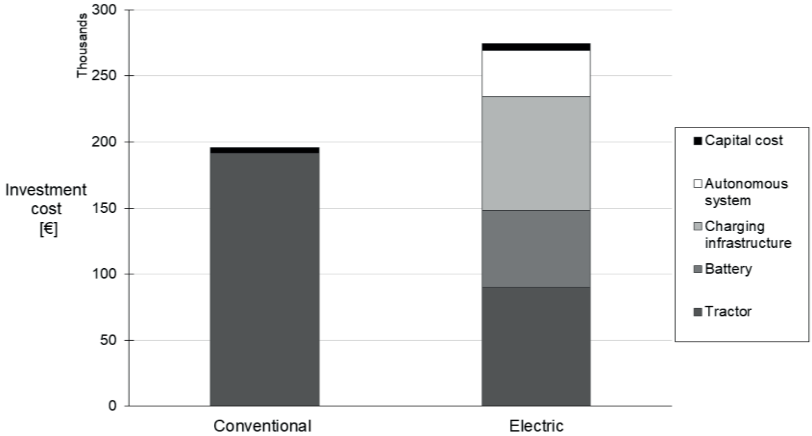

Figure 24. Investment cost for the conventional and electric tractor scenarios.

5.3.2 Operating costs

The investment costs were recalculated over component lifetimes to ownership cost, or annuity, and included as an operating cost (**Paper II**), along with the cost of operator/s, maintenance, timeliness, fuel and potential yield loss from soil compaction (Figure 25).

Electrification of the driveline had several apparent effects. First, the annuity for the electric system was much higher (22,500 € y^{-1}) than for the conventional case (15,500 € y^{-1}). Second, there was a reduction in fuel cost due to the higher efficiency of the driveline, as the fuel price per unit of energy was very similar for electricity and diesel (0.076 € kWh^{-1}). The electric driveline analysed in this thesis had theoretical potential to reduce energy use by 75%, but the more frequent refuelling compared with the conventional system, increased road transport and the net energy reduction in the studied scenarios was 62%. This resulted in a cost reduction from 11,700 € y^{-1} to 4,400 € y^{-1} when using field test data for diesel fuel consumption (Lindgren et al., 2002). Finally, the reduction in maintenance requirement was minor but non-negligible (2,900 € y^{-1}).

The impact of vehicle autonomy was evident as a reduction in timeliness cost and operator cost. The increased work rate led to improvement in timeliness, as discussed in section 5.2.1. Two small autonomous battery-electric tractors had higher machine capacity than the conventional system and this allowed earlier crop establishment and more timely fieldwork operations. The reduction in operator cost was due to a combination of reduced fraction of time the machine needed to be operated by a human driver and increased work rate reducing the total number of hours the machine was active. Despite the high level of autonomy, the operator cost was not eliminated, but reduced by 41%. Overall, autonomy reduced the timeliness cost by 3,000 € y^{-1} and the operator cost by 6,100 € y^{-1} compared with the conventional scenario. More importantly, autonomy of the electric tractors was a key technology in making the electric driveline competitive, as the main cost disadvantages of manned electric tractors (high operator costs and low fieldwork rate of work) were eliminated, resulting in a total operating cost reduction of 32-37%.

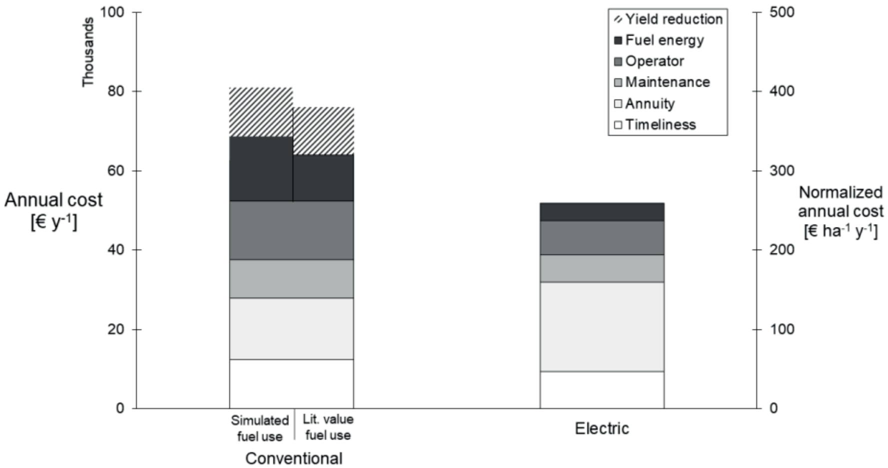

Figure 25. Total annual cost and normalised annual cost for the two scenarios, with both simulated and field-test fuel use included. Soil compaction impact in the conventional scenario is indicated as cross-hatched squares.

5.4 Environmental impact

The model results were split into gate-to-gate (GTG) results and cradle-to-grave (CTG) results, where GTG is the life cycle from material to finished product at the factory gate, focusing on material, manufacturing and assembly, and CTG is the entire vehicle life cycle, including production, use and recycling/disposal. The midpoint results used both CTG and GTG, while the endpoint results focused exclusively on CTG.

5.4.1 Midpoint results

Gate-to-gate (GTG)

In the manufacturing and assembly processes for the electric tractor scenario, production of the NCA-C Li-ion battery had a significant impact (42-83%) in all impact categories analysed in the GTG scope, except for ozone depletion (**Paper IV**). The impact and source in the most common impact category, global warming, are shown in Figure 26. The battery had a climate impact of 15.5 kg CO_2eq kg^{-1} or 155 kg CO_2eq kWh^{-1}. This was slightly above common literature values of 120-133 kg CO_2eq kWh^{-1} for NCA-C batteries (Bauer, 2010; Le Varlet et al., 2020; Samaras & Meisterling, 2008) and above average but in line with measured values for general Li-ion batteries with non-specified or aggregated chemistries (range 61-175 kg CO_2eq kWh^{-1}) (Aichberger & Jungmeier, 2020; Dai et al., 2019; Emilsson & Dahllöf, 2019; Hischier et al., 2009).

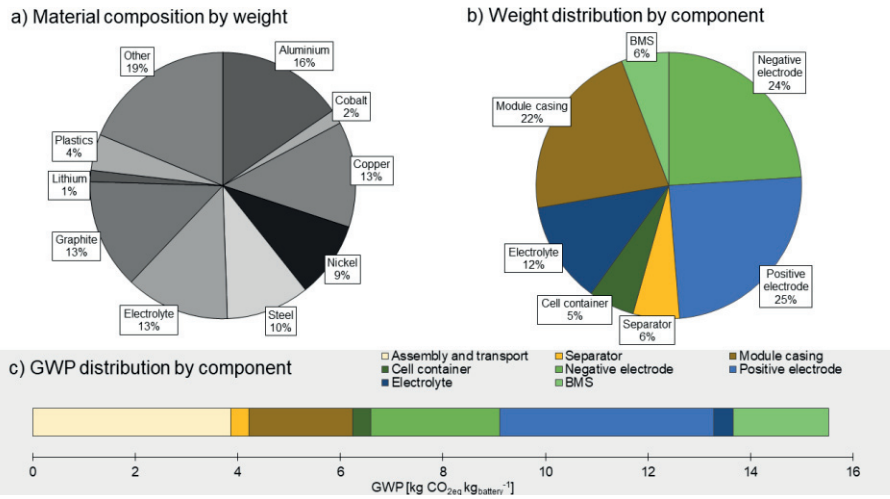

Figure 26. Climate impact data for the NCA Li-ion battery, showing a) material composition, b) weight distribution and c) global warming potential (GWP) impact per component.

Other key impacts during production of the electric tractor system were the glider (vehicle w/o driveline) and the charging infrastructure, as they included many high-impact metals and many processes and had high weight. The electric motor and the autonomous system components had a comparatively small total impact, even though they had a high impact per weight unit, as their total weight was low compared with that of the batteries or the charging infrastructure (Figure 27).

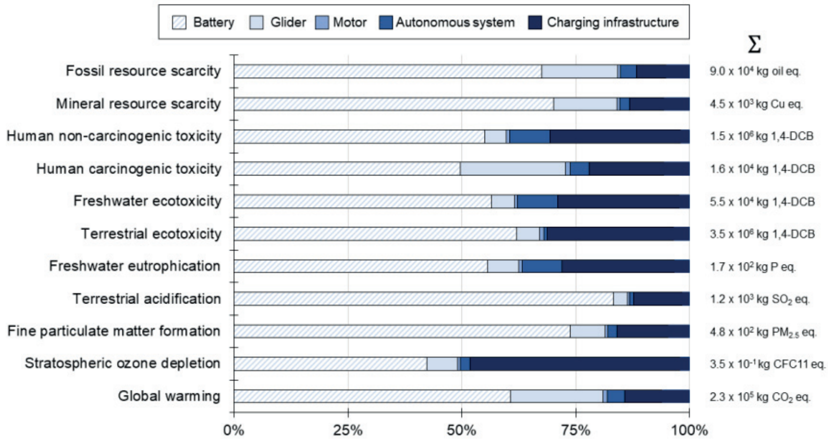

Figure 27. Gate-to-gate (GTG) results for the autonomous electric tractor scenario, showing the climate impact in the 11 selected impact categories and the impact of the main vehicle components.

The conventional tractor scenario had a less complex impact distribution, as most of the impacts arose in the vehicle production and assembly processes. Using a pre-defined dataset inventory from EcoInvent (Nemecek & Kägi, 2007), although verified, meant that some resolution of components was lost and impacts were aggregated. On comparing the GTG results for the conventional and autonomous electric tractors, the latter had a higher midpoint GTG impact in all categories studied (Figure 28). As in the cost comparison, the environmental impact burden of the autonomous electric vehicle was also higher in the investment phase. Much of this impact originated from production of four 100 kWh (roughly 4,000 kg) batteries for the system. A finding worth noting is that the GTG global warming impact of the autonomous electric vehicle was close to that of the conventional vehicle (3-17% higher for the electric tractor). In previous studies, the high impacts of manufacturing electric vehicles (batteries in particular) have been identified as an impediment to electric vehicles fulfilling their potential to reduce climate impacts. The similar values obtained for conventional and electric tractors in this thesis indicate that this might not be the case for agricultural machinery.

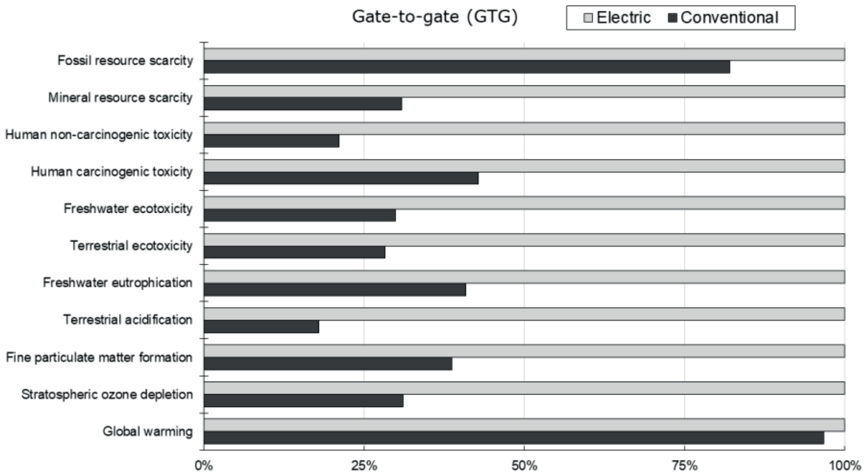

Figure 28. Comparative gate-to-gate results in the 11 selected climate impact categories for the autonomous electric tractor (light grey) and conventional tractor (dark grey) scenarios.

Cradle-to-grave (CTG)

The CTG analysis included the use and EoL phases, in addition to materials and production. The results obtained for the conventional tractor scenario indicated that the energy used as fuel (diesel) was highly impactful in all categories and was the main contributor in all but one impact category (Figure 29). For the autonomous electric tractor system, the battery and charging infrastructure contributed heavily to the impacts, in addition to the electricity impact. The vehicle, including the electric motor, glider, chassis, repairs, maintenance, driveline and autonomy components, had a minor effect, due to the low vehicle weight (3,527 kg) compared with the conventional tractor (10,800).

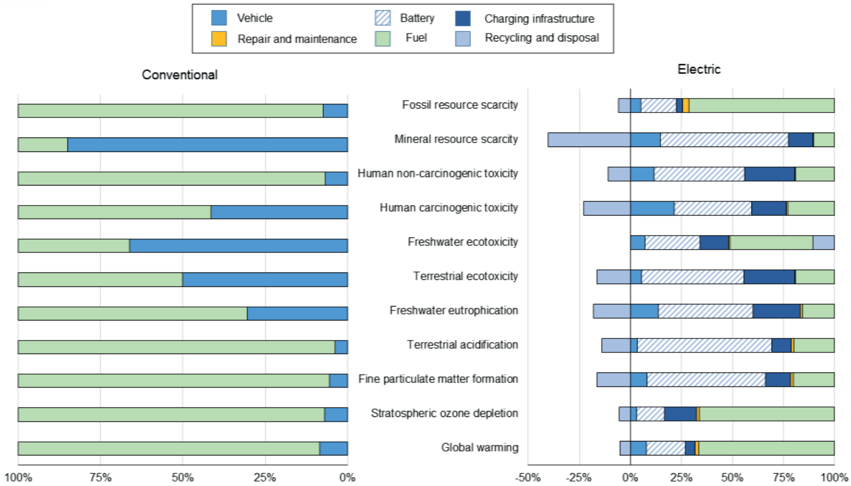

Figure 29. Cradle-to-grave (CTG) climate impact in the 11 selected impact categories for (left) the conventional tractor scenario and (right) the autonomous electric tractor scenario. For the conventional scenario, repair, maintenance and disposal are included in "Vehicle".

The conventional tractor scenario had a higher climate impact in eight of the 11 selected impact categories (Figure 30). The autonomous electric tractor scenario had a higher impact only in terrestrial ecotoxicity, freshwater ecotoxicity and mineral resource scarcity, where the large quantity of batteries needed in the system was highly impactful. Further normalising the impact values per hectare and year, assuming a 15-year vehicle lifetime and 200 hectares of arable land worked, gave a climate impact of 77 and 269 kg CO_2eq ha^{-1} y^{-1} for the autonomous electric tractor and conventional tractor scenario, respectively.

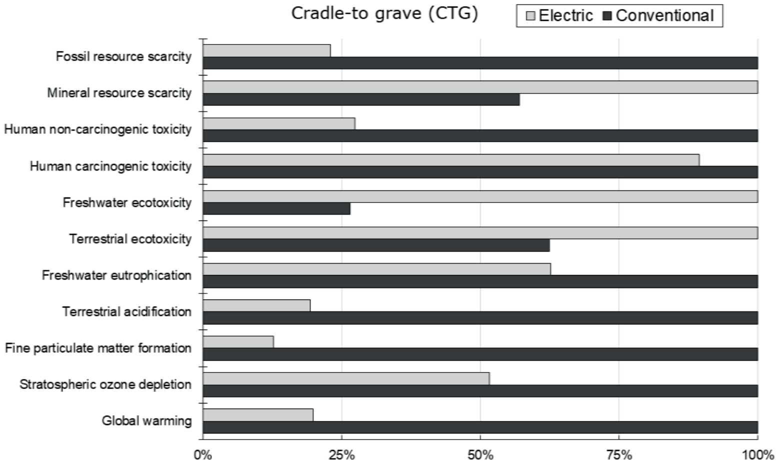

Figure 30. Comparison of cradle-to-grave climate impacts in the 11 selected categories for the autonomous electric (light grey) and conventional (dark grey) scenarios.

Table 8: *Gate-to-gate (GTG) and cradle-to-grave (CTG) life cycle assessment midpoint results in the 11 selected categories for the autonomous electric tractor and conventional tractor scenarios*

	GTG		CTG		
Impact category	Conv.	Elect.	Conv.	Elect.	Units
Global warming	8.7	9.0	10.2	2.3	10^5 kg CO_2 eq.
Stratospheric ozone depletion	0.4	1.3	5.9	3.5	10^{-3} kg CFC11 eq.
Fine particulate matter formation	0.2	0.5	3.3	0.5	10^3 kg $PM_{2.5}$ eq.
Terrestrial acidification	0.2	1.2	5.4	1.2	10^3 kg SO_2 eq.
Freshwater eutrophication	76	185	250	174	kg P eq.
Terrestrial ecotoxicity	1.0	3.6	2.0	3.5	10^6 kg 1,4-DCB eq.
Freshwater ecotoxicity	0.9	3.0	1.4	5.5	10^4 kg 1,4-DCB eq.
Human carcinogenic toxicity	0.7	1.6	1.7	97.9	10^4 kg 1,4-DCB eq.
Human non-carcinogenic toxicity	0.03	0.16	4.8	1.5	10^6 kg 1,4-DCB eq.
Mineral resource scarcity	2.1	6.8	2.5	4.5	10^3 kg Cu eq.
Fossil resource scarcity	2.5	3.1	34.0	9.0	10^4 kg oil eq.

In the most commonly used midpoint impact category (global warming), the autonomous electric tractor scenario had 23% of the impact of the conventional diesel tractor system. As 91% of the climate impact for the conventional tractor scenario and 67% for the autonomous electric tractor scenario derived from the fuel, the type, mix and source of fuel were factors with high significance for the global warming impact. In this thesis, marginal Swedish electricity mix was assumed to be used for the autonomous electric tractors and in manufacturing, assembly and EoL .

A comparison between different fuel sources was made, considering both the unit climate impact of fuels and the impact per useful unit, after the different driveline efficiencies had been taken into account (Figure 31). Diesel had a lower climate impact per unit than electricity produced from natural gas, hard coal and the global electricity mix (which consists of majority natural gas and coal and is comparable to the European mix and Swedish marginal electricity). However, after driveline losses, diesel had a higher impact than all electricity mixes except hard coal, even when 17% HVO blend-in was assumed. HVO from Swedish feedstock, considered a sustainable ICE option (Källmén et al., 2019; Soam & Hillman, 2019), had a higher impact than both Swedish marginal and European electricity. Renewable electricity and the Swedish average mix gave a significantly lower climate impact per useful energy unit than any ICE option (Figure 31).

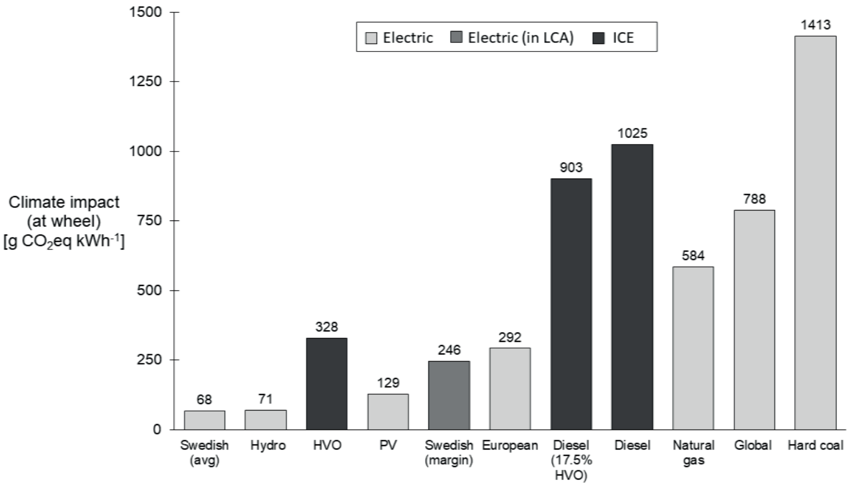

Figure 31. Climate impact for different fuel mixes and origins, shown as useful energy (at wheel, after driveline losses).

5.4.2 Endpoint results

The endpoint results (Figure 32) strongly indicated that the autonomous electric tractor scenario had a lower impact than the conventional tractor, regardless of whether field test energy demand or simulated demand was used in calculations. On weighing all the midpoint factors together and converting them to their damage categories, the impact of the autonomous electric tractor scenario was 75-83% lower for human health, 54-68% lower for ecosystem impacts and 71-80% lower for resource scarcity. The damage category “resource scarcity” was weighed from the fossil and mineral resource use midpoint categories, and even though the autonomous electric scenario had high mineral resource use, the fossil resources used for fuel in the conventional case significantly outweighed this. Collected to a single score, the reduction was 74-82%.

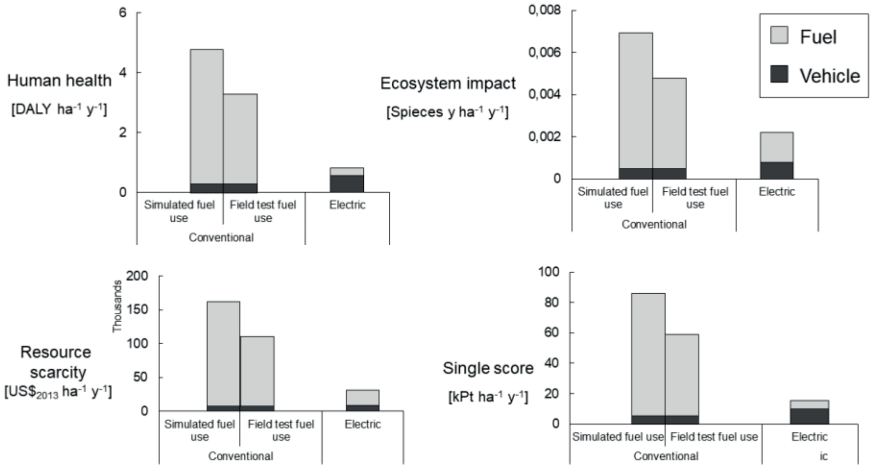

Figure 32. Damage category impacts for the autonomous electric tractor and conventional tractor scenarios, with simulated and field test fuel use included for the conventional scenario. Impact is divided between vehicle (dark grey) and fuel (light grey), where vehicle includes infrastructure, disposal, repair and maintenance.

Soil compaction

The soil compaction component of the environmental impact was distributed into two main factors; increased amount of fuel used and loss of yield. The increased amount of fuel for the conventional case contributed to a 26% increase in the climate impact and a 26-27% increase in the different damage categories (**Paper V**). It is important to note that this impact was specific to the soil type, which was clay-rich.

General comparison & verification

The loss of yield effect of 8% due to soil compaction for the conventional tractor compared with the lighter autonomous electric tractors was only apparent when using a secondary functional unit of loss per mass (kg) of grain produced (Figure 33). This resulted in global warming potential of 0.057 kg CO_2eq kg^{-1} grain, or 0.039 kg CO_2eq kg^{-1} grain, without soil compaction effects. For comparison, the autonomous electric tractor scenario had an impact of 0.015 kg CO_2eq kg^{-1} grain (**Paper V**). This can be compared to a total value of 0.22-0.70 CO_2eq kg^{-1} grain for Swedish wheat production reported in the literature (Henryson et al., 2020; Moberg et al., 2019; Röös et al., 2011), with a value for machinery production and use of 0.07 kg CO_2eq kg^{-1} grain reported by Moberg et al. (2019). The results for the conventional tractor are therefore in line with literature values, and the autonomous electric tractor showed potential for a significant reduction in climate impact.

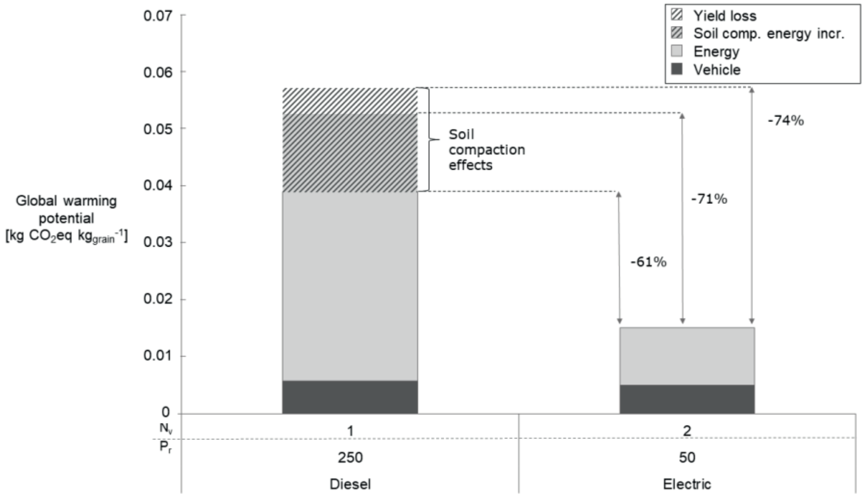

Figure 33. Global warming potential per unit of grain produced for different levels of soil compaction effects in the conventional diesel tractor and autonomous electric tractor scenarios (Paper V).

5.5 Scenario and sensitivity analyses

In order to broaden the scope slightly and show the outcomes of different technological choices and component sizes, other possible scenarios were explored in addition to the two primary scenarios. These scenarios are described in full in **Papers I, II** and **V**, and that analysed in **Paper V** is also discussed below.

5.5.1 Scenario analysis

The different scenarios simulated in **Paper V** included tractor systems of different sizes, fuel energy, number of vehicles and degrees of autonomy (Table 9), in order to cover other system structures.

Table 9: *Key parameters used in the different scenarios analysed in Paper V. The two main scenarios discussed in this thesis are shown in italic font*

Fuel	No. of vehicles (N_v)	Rated power (P_r, [kW])	Energy carried [kWh, (l)]	Extra battery packs	Working time [h d^{-1}]	Mass, incl. batteries [kg]
Diesel	*1*	*250*	*4,684 (463)*	-	*10a*	*10,800*
	1	250	4,684 (463)	-	24	10,800
	2	50	1,315 (130)	-	24	2,527
Electric (BES)	*2*	*50*	*100*	*2*	*24*	*3,527*
	3	50	100	2	24	3,527
	1	250	200	2	24	12,800

[a]Driver.

Performance

Compared with the machine capacity of the manned diesel tractor, which was used as a benchmark for adequate machine capacity, all other scenarios had a lower active time requirement (Figure 34). This indicates that autonomy can be a useful tool for increasing machine work rate in almost any system, enabling more timely crop establishment. It was also found that autonomous diesel tractor scenarios in general had a higher rate of work and spent a larger fraction of their time on fieldwork than autonomous electric tractor scenarios. Two smaller battery-electric tractors had a lower time requirement than one large electric tractor, even though their time distribution was very similar, indicating that using two tractors can give a more efficient system structure.

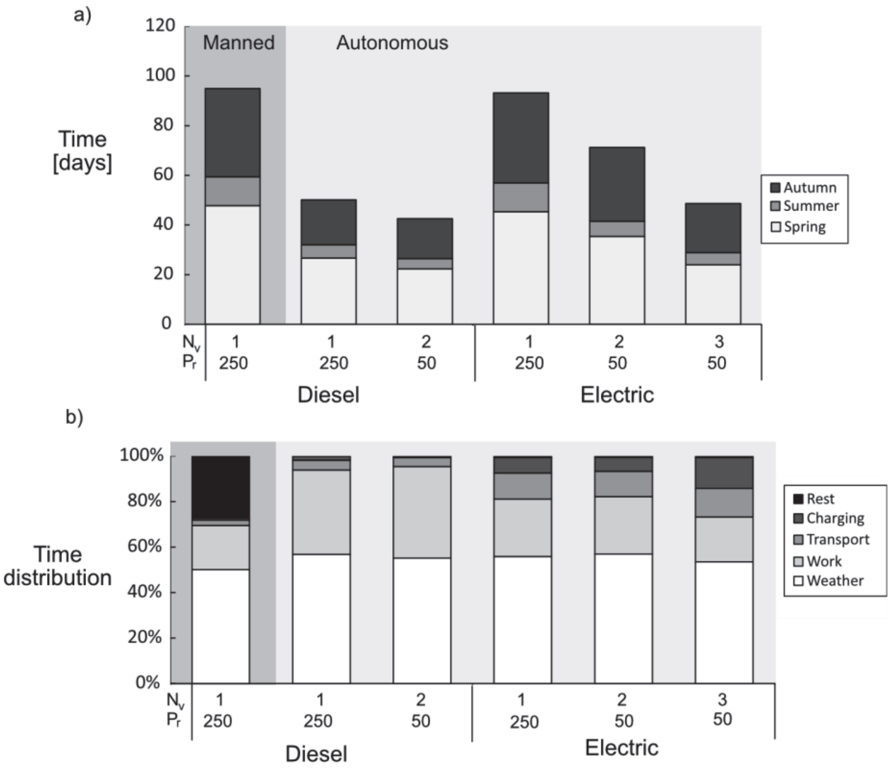

Figure 34. Results of scenario analysis for six scenarios differentiated by number of vehicles (Nv), rated power in kW (Pv) and fuel (diesel, electric). (a) Length of working periods and (b) time distribution. All values are 11-year averages (2008-2018).

Costs

The annual cost varied greatly between the different scenarios, with heavier vehicles having the highest annual costs, mainly due to soil compaction effects (Figure 35). When soil compaction effects were disregarded, the autonomous diesel tractor scenarios had a lower cost than the autonomous electric tractor scenarios, mainly due to reduced annuity and operator costs, while the autonomous electric tractor scenarios reduced fuel and maintenance. The increased machine capacity (see Figure 34) reduced the timeliness cost, but was not critical. All scenarios had a lower cost than the 250 kW autonomous electric tractor and the manned diesel tractor, with the system comprised of two small autonomous diesel tractors having the lowest annual cost, followed by the main autonomous electric tractor scenario. The scenario with three autonomous electric vehicles provided increased machine capacity at the cost of increased annuity.

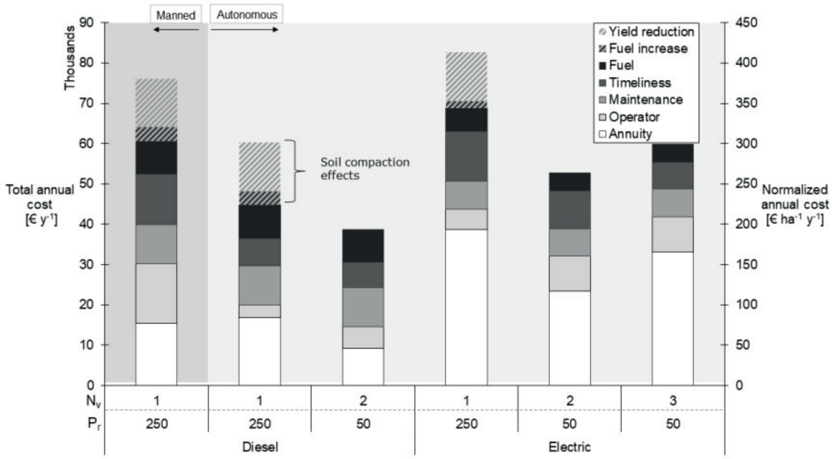

Figure 35. Total annual cost of six scenarios differentiated by number of vehicles (N_V), rated power (P_v) and fuel (diesel, electric), distributed per category of costs (left axis) and normalised to annual cost per hectare (right axis).

Environmental impact

The LCA results showed that the autonomous electric vehicle systems had a lower impact in terms of climate impact and in the damage categories human health, ecosystem impact and resource scarcity than the diesel vehicles (Figure 36). The only exception was the 50 kW diesel vehicle in the "ecosystem impact" damage category, where it had slightly lower impact than the largest autonomous electric tractor scenario. In all other metrics, the reduced fuel impact of the autonomous electric tractors was shown to be defining. However, those scenarios also had a large manufacturing impact, mainly due to the large amount of batteries manufactured. Overall, therefore, the two-vehicle system had the lowest impact, as it did not require as much manufacturing as the other electric tractor scenarios. The reduction in fuel impacts had a two-fold effect, as the increased energy efficiency led to a higher amount of energy being used for useful work and as electricity generally had a lower impact per unit of fuel compared with diesel.

Using low-impact fuel efficiently, having a low manufacturing impact and having low vehicle weight seemed to be the most impactful factors for low environmental impact.

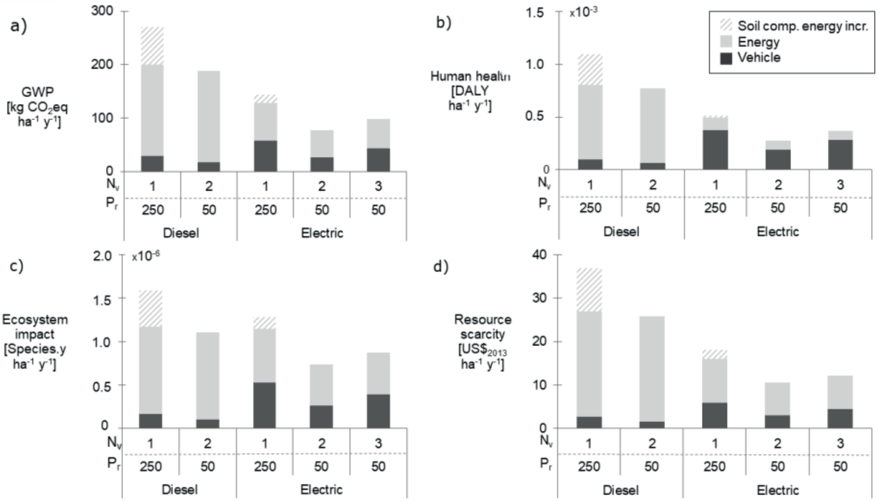

Figure 36. General life cycle assessment (LCA) results showing (a) global warming potential (GWP) and impact in the damage categories (b) human health, (c) ecosystem impact and (d) resource scarcity in six scenarios differentiated by number of vehicles (N_V), rated power (P_V) and fuel (diesel, electric). End-of-life, infrastructure, repairs and maintenance are included in “Vehicle”.

5.5.2 Sensitivity analysis

Sensitivity analysis was performed in order to analyse the impact of individual parameters on system performance (**Paper I**), annual cost (**Paper II, V**) and environmental impact (**Paper IV, V**),. This was done as a way of verifying the assumptions made and assessing parameter variation or uncertainty. The sensitivity analysis of system performance (**Paper I**) showed that increasing the individual parameters had a diminishing return in terms of effectiveness. The sensitivity analysis of cost (**Paper II**) identified rate of autonomy, operator cost and investment cost of the tractor as impactful factors, while also showing that the battery investment was comparatively less impactful, in contrast to the case for passenger vehicles (Delucchi & Lipman, 2010). The sensitivity analysis of environmental impacts (**Paper IV**) showed that choice of fuel was the main factor to consider, with battery size and vehicle lifetime also being impactful. Analyses performed in **Paper V** confirmed these findings.

6. Further discussion

The performance of the agricultural vehicle systems analysed in this thesis showed significant dependence on location, farm type and the scope of the analysis. Therefore the applicability of the findings for real-world operations and for other vehicle systems, farm types, locations and technologies can be questioned. However, the conclusions reached were in accordance with those found in previous simulations or calculations for similar systems (Baek et al., 2020; Lampridi et al., 2019), and the individual findings were verified whenever possible. While it bears repeating that other system boundaries, scopes or assumptions might produce different results, the general changes and conclusions should be generally applicable to similar systems. As such, they may prove useful for future research on electric vehicles in agriculture. In addition, the decision was made to perform a simulation-based study due to a lack of feasible alternatives for a study of this scope. This made it possible to conduct a more explorative study with a wide scope, which also gave the opportunity to assess system choices that had a large impact and provided flexibility in changing parameters to find general connections and trends.

In the short-term, transition to biofuel has been suggested as an effective way to reduce GHG emissions from transport and machinery, as commonly available biofuels can often be used in existing vehicles, with HVO replacing diesel being of particular interest to the agriculture sector (Soam & Hillman, 2019). It could be argued that the most logical subject of research would be biofuels powering autonomous vehicles, providing low GHG emissions and strong economic potential without the challenges of battery drivelines. Biofuel is undoubtedly a good solution to reduce GHG emissions in the short-term, to reach environmental goals set for the coming decade (European Comission, 2018; The Government of Sweden, 2013) and as an important component in a fossil-free vehicle fleet. However, biofuel vehicles are already close to wider market implementation and are at high technology readiness level, and thus require less research and more adaptation. In addition, electric drivelines provide further benefits over ICEs, regardless of fuel. Examples include higher efficiency, lower environmental impacts, the potential for local production and cheaper fuel. IPCC (2022) argues that electric vehicles have large GHG emissions reduction potential, while biofuels can provide similar effects in the short- and medium-term. In line with this, the scope of the research in this thesis was on autonomous electric tractors, as this is a more transformative technology where the knowledge gap is wider and more research is needed.

An important consideration is that the choice and structure of systems compared in this thesis are at different technology readiness levels (European Comission, 2019). The conventional diesel tractor system is widely used and has been developed over decades. The autonomous electric tractor system, on the other hand, was based on a combination of different technologies that are assumed to become operational in the near future, in contexts close to contemporary farming. Common current-day technologies were used for autonomous systems, electric motors and drivelines, batteries and charging stations. By using current technology, costs, emissions and component parameters for a near-future system, some accuracy in the results was lost, as future developments were omitted. However, sensitivity analysis was performed where possible (**Papers I, II, IV** & **V**) to assess the potential impact of changing different parameters. Transformative technologies are seldom competitive early in their development, especially when compared with established technology. The general trend is for new technologies to become cheaper, more efficient and have better-developed supply chains as they become more widely used (Arvidsson et al., 2017). As battery-electric vehicles and autonomous vehicles are both of high market interest, this is a likely future trajectory for these technologies. As an example of this trend, the cost of Li-ion vehicle batteries has decreased by 89% over the past 10 years (IPCC, 2022). In comparison, fossil fuels and ICEs are unlikely to see significant further development and fossil fuels are expected to be significantly less used (through policy changes or market incentives) in the near future (European Comission, 2018; IPCC, 2022). Due to the different nature of the systems (both in degree of autonomy and type of fuel), it is not certain that the autonomous battery-electric tractor system will be used in the same manner or have the same business model as the conventional tractor system when fully developed, as transformative technologies often lead to new modes of use. However, trying to predict future trends is a difficult endeavour, so contemporary technology and trends were used as an approximation in order to fulfil the research aims of this thesis.

7. Conclusions

This thesis compared a conventional system of manned diesel tractors with a system of smaller autonomous battery-electric tractors, in simulation analyses of a 200-ha grain farm in Uppland County, Sweden. Simulations and theoretical analysis proved to be useful tools in assessing future agricultural vehicle systems that cannot yet be field-tested in a practical context due to cost or lack of technological maturity. Such analyses also made it possible to study many different system structures in a flexible and timely way. Using a multi-disciplinary approach that included dynamic simulation, economic analysis and life cycle analysis, potential system effects were studied, general dynamics were identified and recommendations were made on ways to optimise the system in terms of all three metrics analysed (performance, costs and environmental impact). The main conclusions were as follows:

- Autonomous battery-electric tractors were capable of similar or better work rate than a conventional diesel tractor used in contemporary Swedish agriculture in a simulated setting, reducing the active time required for field operations by 17 days per year and allowing a larger fraction of useful work.
- Vehicle autonomy was the main driver behind the improved work rate. Autonomy was required to mitigate the drawbacks of electric vehicles in terms of energy capacity, frequent recharging and slow recharging rate.
- Utilisation of a battery exchange system (BES) was more beneficial than conductive charging (CC), as it shortened recharging times.
- Use of autonomous electric tractors increased the energy efficiency of the vehicle system, with an average driveline efficiency of 74% from charging station to implement, due to higher efficiency in components, compared with 26% energy efficiency for the conventional diesel tractor. This reduced the energy use from 153,800 kWh y^{-1} (76 L diesel ha^{-1} y^{-1}) for the conventional tractor system to 58,500 kWh y^{-1} (equivalent to 29 L ha^{-1} y^{-1}) for the autonomous electric tractor system, a reduction of 62%.
- Lower annual cost of the autonomous electric tractor system made it competitive relative to the conventional diesel tractor system. While the

electric tractor had higher investment cost, autonomy led to lower operator cost and the electric driveline led to lower maintenance and fuel costs compared with the conventional system. This led to a net reduction in annual costs of 32-37% for the studied system. The cost assumptions for autonomy, batteries, fuel and electricity may be challenged, but the conclusion after economic scenario and sensitivity analysis was that equal or lower operating costs are possible with autonomous electric tractor systems.

- In LCA, the autonomous battery-electric tractor system reduced the climate impact by up to 74% compared with the conventional diesel tractor system. The main driver behind this was emissions associated with fuel use, which was a significant contributor to the climate impact for agricultural machinery use. Since the Swedish marginal mix assumed in the analysis had a lower impact per energy unit compared with diesel and the electric driveline used less energy in total, this led to a large reduction in climate impact. The choice of fuel was by far the most impactful factor for both systems.
- Utilising a full LCA with LCI, LCIA and 18 impact categories gave high-resolution results and clearly identified battery manufacturing and fuel use as two hotspots for emissions and damage impacts. In eight out of 11 impact categories studied in detail, the conventional system had higher impacts. In the human health, ecosystem impact and resource scarcity damage categories, the autonomous electric tractor system gave 54-80% lower impact than the conventional system, showing good potential to reduce the environmental impacts of agricultural machinery, especially if low-impact electricity is used.
- Reduced vehicle weight was shown to be an important additional benefit of the autonomous electric tractors compared with the conventional diesel tractor, especially for the clay-rich soil in the study area (Uppland County). Use of vehicles weighing 3,500 kg instead of 10,800 kg was possible due to vehicle autonomy, which led to avoidance of further soil compaction. This effect alone may not be a strong enough incentive for a technology shift, but it provided a strong additional argument by amplifying existing trends.
- Batteries were found to be an important technological choice and warrant further research. Simulated battery ageing as a function of cycling showed different rates of ageing depending on the charging rate

used for charging/discharging and led to optimisation of the battery towards a longer cycle life. The chosen 100 kWh NCA battery had a cycle life of 7760 cycles before reaching EoL and being replaced. From a cycle-based capacity fade perspective, a larger battery with a lower effective charging rate was preferable to smaller batteries that are cycled more intensively. On-site battery storage was shown to have some benefits, but the load of electric tractors was insufficient to reach feasibility.

- Good battery sizing and management were shown to be critical from a work efficiency, economic and environmental perspective. For a 200-ha farm, a 100 kWh battery provided a high work rate, a low rate of cycle ageing and a good balance (both economically and environmentally) between initial investments and effective use. These factors were linked, *i.e.* an efficiently used battery with a long time before replacement was both economically and environmentally sound.
- All metrics analysed benefited from being optimised as a system and not as individual components, since increasing the value of individual parameters did not resolve bottlenecks and often suffered from diminishing returns. A balanced approach to number of vehicles, batteries and charging stations and vehicle power, carried energy content and charging power was the most beneficial solution, allowing non-productive time to be kept at a minimum while not investing in unused overcapacity. This was confirmed in analysis of likely alternative scenarios involving other possible system structures, where the autonomous battery electric tractor system showed balanced results for all metrics.

Overall, this thesis and the individual papers showed that autonomous battery-electric tractors can be economically and environmentally competitive with contemporary diesel tractors in the near future. By combining the battery-electric driveline with autonomy, the benefits from both can be used to greater effect than either by itself.

8. Future research

Research is a continuous and iterative process where each answer to a question leads to greater understanding and also new questions. Some additional questions and lines of research requiring further exploration emerged during the work in this thesis.

The work presented in this thesis is theoretical, so it is important to explore similar vehicle systems in field tests. There have recently been some successful tests on similar systems (Fendt, 2017; Grimstad & From, 2017; Young et al., 2018), but field tests on all-purpose autonomous electric implement carriers are rare. Verification and testing is needed to confirm the hypothesis and conclusions presented in this thesis and to provide further insights into applied use of electric and autonomous fieldwork tractors. It would also bring the technology closer to farmers, who were among the main intended beneficiaries of the research in this thesis.

On moving from theoretical research and simulation to successful application, additional fieldwork types should be simulated and preferably field-tested. It was found in **Papers I, II** & **V** that heavy soil tillage operations such as harrowing, cultivation and ploughing were responsible for much of the final energy use and in-field time. Exploring fieldwork methods with lighter tilling or no-till techniques could be highly beneficial for the autonomous electric vehicle systems described here, as heavy field operations have also been cited as a limiting factor in electrification of tractors due to their high power need (Caban et al., 2018; Moreda et al., 2016). It is claimed that the high accuracy of autonomous or heavily driver-assisted agricultural vehicles could provide sufficient field resolution to apply implements to specific plants (Gonzalez-de-Santos et al., 2017; Mousazadeh, 2013), rather than specific rows as is done today. This could further reduce the power requirement of field implements and should be explored in future research.

This thesis focused on battery-electric vehicles, but other fuel choices are possible. HVO and other biodiesels have a high technology readiness level and are already available on the market as a drop-in replacement for diesel with lower GHG emissions (Källmén et al., 2019). For this reason, they were not included in this thesis, but they can be a valid short-term replacement for diesel without the scale of system change necessary for electric tractors.

Other low-emission biofuels are also interesting for further research, as they are close to implementation and can provide a good replacement for diesel in the near future. Hydrogen, used in fuel cell tractors, is another interesting technology choice, as it would combine the high efficiency of the electric driveline with energy-carrying capacity similar to that normally found in conventional tractor fuels. Its use would require substantial infrastructure, both locally and nationally, but it would entail a high degree of GHG reduction compared with diesel and it could be produced nationally in a low-fossil process (Cetinkaya et al., 2012; Iannuzzi et al., 2021). Although some hydrogen-powered tractors have been tested in pilot projects, further research is needed as the most probable replacement for diesel in agricultural machinery will not be one fuel, but a combination of several biofuels and electricity-based fuels.

Paper III explored the feasibility of storing energy locally on-farm and showed that it depended heavily on secondary uses for the stored energy. Further research into energy storage on-farm is needed, particularly where additional energy loads use the stored energy and where changes in electricity price over periods (both over the day and over seasons) are taken into account.

Vehicle autonomy was included in the systems analysed in this thesis in a simplified manner, both technically and legally, to explore its impact once fully integrated in fieldwork. The steps necessary for this transformation should be studied carefully (Lajunen et al., 2018). There has been much research on technological components, ethical considerations and the economic potential of autonomous vehicles and all these aspects warrant continued research. In addition, the management aspect, possible business models and field tests to determine reasonable rates of autonomy require further exploration, as the work in **Paper II** suggests. In this thesis, it was assumed that the tractors were mainly autonomous and were wholly owned and operated by the farmer, with no extra services required. However, it is likely that autonomous vehicles would have different business or management models (subscriptions, rented services, leases, external operators *etc.*). Autonomy was found to be a key enabling technology for electric fieldwork tractors (**Paper I & II**) and the viability of using autonomy requires a good technological foundation and a solid understanding of the non-technical aspects. Studying non-technical barriers to implementation and market penetration could shorten the time to widespread operational use.

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Popular science summary

Agriculture is important for producing food, feed and other products, but the tractors used in agriculture today run on diesel, which has a negative climate effect. One way to reduce this effect is to change fuel to electricity, as it has less negative climate effects than diesel, but this presents some challenges. Batteries can hold a hundred times less energy per unit weight than a fuel tank, so an electric tractor would work a shorter time and need to return from the field to refuel more often than a diesel tractor. This would be expensive and would give a slower work rate than for diesel tractors. One solution to this would be to make the tractors self-driving, or autonomous. This would allow them to work more hours per day and the frequent trips back to the farm would not be as expensive, as a driver would not need to be paid to be present during that unproductive time.

This thesis examined the effect of autonomous electric tractors on fieldwork by considering a system with two 3-tonne tractors with rated power of 50 kW, 100 kWh batteries and on-farm charge and exchange of batteries. This system was compared to a manned modern 10-ton 250 kW tractor run on diesel. Since autonomous electric tractors are rare and since field testing would be cumbersome, expensive and limited, they were instead simulated using a computer model based on a 200-ha grain farm in Sweden and conventional implement use. Simulations of both the conventional tractor system and an autonomous battery-electric tractor system were used to evaluate whether the tractors could get all field operations done in time, the cost, the environmental impact (climate warming and other categories), the overall structure of the different systems and the challenges they faced.

The results showed that the autonomous electric tractors were able to complete fieldwork operations in the same time, or faster, than the conventional tractor. This was mostly because the autonomous tractors could

work for much longer. Being electric slowed the tractors down, since they could only work for a few hours before returning to the farm for recharging, but being autonomous compensated for this. It was also important to have as little unproductive time as possible, such as queueing, charging, driving to or from the field, and waiting for the soil to dry up.

The autonomous electric tractors had a larger initial investment cost, mainly since charging stations had to be built and large batteries are expensive. However, the electric drivelines used less fuel and required less maintenance, while being autonomous reduced the driver costs and made it possible to use lighter tractors with less soil compaction. These factors gave the autonomous electric tractors similar or up to 37% lower total yearly costs compared with the diesel tractor.

The environmental impact of the systems was calculated over the entire lifetime of the tractors, from manufacturing to use and finally recycling/disposal. Eleven different environmental impact categories were considered, as well as damage to human health, ecosystems and resources. Manufacturing the batteries had a clear negative environmental impact, as it required much energy and many different materials. However, fuel use had the largest impact in almost all categories. Diesel has a greater negative impact than electricity in general, and especially Swedish electricity, and it was the largest contributor to the negative climate impact of the diesel tractor system. By switching from diesel tractors to autonomous battery-electric tractors, the climate impact could be reduced by up to 74%, and similar reductions could be made in damage to human health, ecosystems and resource use.

Simulations comparing autonomous battery-electric tractors and diesel tractors showed that the electric tractor system could carry out fieldwork with equal or improved performance, at equal or lower cost, with clear environmental benefits. By combining the battery-electric driveline with autonomy, the benefits from both were used in a better way than each on its own.

Populärvetenskaplig sammanfattning

Lantbruk är en viktig sektor som producerar mat, foder och andra viktiga produkter. De maskiner som används i dagens lantbruk använder nästan uteslutande diesel som bränsle, vilket har en negativ klimatpåverkan. Ett sätt att minska denna påverkan är att byta bränsle till elektricitet, eftersom den har mindre klimatpåverkan jämfört med diesel. Det bytet kommer dock med några utmaningar. Batterier kan hålla en hundradel så mycket energi per viktenhet som diesel gör, vilket betyder att en batteritraktor kan arbeta kortare tid ute på fälten och behöver tanka oftare än en dieseltraktor. Det kan bli dyrt och leda till att arbetstakten blir långsammare än dagens traktorer.

En lösning är att göra traktorerna självkörande, även kallat autonoma. Det skulle innebära att de kan arbeta fler timmar än en människa och att oftare köra tillbaka till gården för att ladda skulle inte vara så dyrt eftersom man inte skulle behöva betala en förare under tiden.

Den här avhandlingen har som mål att undersöka vilken effekt dessa autonoma eltraktorer skulle kunna ha på fältarbete i svenskt lantbruk. Maskinerna som undersöktes var två stycken självkörande 3-tons traktorer med 50 kW motoreffekt och 100 kWh batterier (motsvarande 10 liter diesel). De jämfördes med en 10-tons traktor med 250 kW motoreffekt, som drevs på diesel och hade en förare. Eftersom det inte finns många självkörande eltraktorer och eftersom fälttester snabbt skulle bli dyrt och begränsat i vad man kan testa så simulerades fordonen med hjälp av en datormodell. Modellen byggde på en svensk spannmålsgård i Uppland som brukade 200 ha med en konventionell odlingsmetodik. Både en konventionell dieseltraktor och eltraktorerna simulerades. Studien undersökte om traktorerna fick alla sysslorna gjorda i tid, hur mycket det kostade och vilken miljöpåverkan det bidrog med (både i klimatpåverkan och andra faktorer).

Den undersökte också hur maskinsystemen fungerade och vilka utmaningar de stötte på.

Det visade sig att de autonoma eltraktorerna kunde utföra fältarbeten på liknande eller kortare tid än dieseltraktorerna. Detta berodde främst på att traktorerna var självkörande, eftersom de då kunde arbeta under längre tid. Batteridrivlinan saktade ner takten, då de bara kunde arbeta ett fåtal timmar innan de behövde återvända till gården för laddning, men autonomin kompenserade för detta. Det visade sig också vara viktigt att ha så lite icke-produktiv tid som möjligt genom att minimera köande, laddtid, transporttid och att vänta på torrare fält.

Investeringskostnaden för eltraktorerna var större än för dieseltraktorn, främst för att man behövde bygga laddstationen och för att stora batterier är dyra. Eltraktorerna använde dock mindre bränsle, behövde mindre underhåll och att de var självkörande betydde mindre förarkostnader och att man kunde undvika markpackning genom att ha lättare fordon. Sammanvägt gjorde detta att eltraktorerna hade liknande eller lägre total årlig kostnad, upp till 37% lägre.

Miljöpåverkan beräknades över hela fordonets livslängd, från tillverkning till användning och slutligen återvinning. 11 olika kategorier av miljöpåverkan beräknades, samt skada på human hälsa, ekosystem och resurstillgång. Tillverkningen av batterier hade en klar negativ miljöpåverkan eftersom det krävdes mycket energi och många olika material. Den största miljöpåverkan för de flesta kategorier visade sig dock bero på bränsleanvändningen, för både diesel och el. Diesel hade generellt en större påverkan än el, speciellt om svensk el användes, och var det som gav störst klimatpåverkan hos dieseltraktorn. Genom att byta från dieseltraktorer till autonoma eltraktorer kunde klimatpåverkan minskas med upp till 74% och med liknande värden för påverkan på humanhälsa, ekosystem och resurstillgång.

Genom att simulera autonoma eltraktorer och jämföra med dieseltraktorer visade det sig att de kunde göra samma arbete med liknande eller bättre prestanda, med liknande eller lägre kostnad och med tydliga miljövinster. Genom att kombinera eltraktorer med teknik för autonomi så kunde båda teknologiernas fördelar användas bättre än var för sig.

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Research Paper

Performance comparison of charging systems for autonomous electric field tractors using dynamic simulation

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A model simulating an autonomous battery electric vehicle system for agricultural field use was created, assuming a 200-ha conventional cereal farm in Swedish conditions. The different subsystems were verified against sources in the literature, field experiments and general common practice. The model was used to compare two different charging systems (conductive charging and battery exchange) for battery electric tractors to each other. A comparative simulation was made with conventional diesel systems (fully autonomous or manned for 10 h d^{-1}). The simulation results indicated that battery exchange was generally a faster system than conductive charging. The results also showed that both electric systems were able to achieve similar active time during spring field operations as a corresponding system of a simulated manned diesel tractor for battery sizes from 50 kWh and charge powers from 50 kW.

1. Introduction

Agricultural field machinery is currently almost exclusively driven by internal combustion engines (ICEs), usually diesels. There are various research paths as regarding renewable drive options, with electric drive seen as a natural step in the evolution of heavy vehicles (Andersson, 2019; Moreda, Muñoz-García, & Barreiro, 2016). In recent years, there have been significant developments in off-road electric drives for mining loaders, excavators, heavy-duty dump trucks and also agricultural vehicles (Moreda et al., 2016).

Battery electric vehicles (BEV) for agricultural field work have been described previously (Alcock, 1983; Engström & Lagnelöv, 2018; Moreda et al., 2016; Volpato, Paula, Barbosa, & Volpato, 2016, p. 162458121), but have not made significant inroads on the market. Previous studies have indicated that conventionally sized field-work tractors with a battery electric drives reduce emissions, increase driveline efficiency and

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Nomenclature

A, B, C	Machine parameters
A	Vehicle front area (m^2)
a	Acceleration ($m\ s^{-2}$)
B_n	Machine/soil ratio parameter
BES	Battery exchange system
BED	Battery electric drive
BEV	Battery electric vehicle
C_D, C_{rr}	Drag and rolling resistance coefficients (decimal)
C_o	Overall rate of work ($ha\ h^{-1}$)
CC	Conductive charging
CC/CV	Constant current/constant voltage
D_F	Distance field-to-farm (km)
D_T	Tillage depth (m)
DES	Discrete Event Simulation
E_R	Rated battery energy content (kW h)
E_B	Battery energy content (kW h)
E_{Road}	Road transport energy requirement (kW h)
FC	Field capacity of soil ($mm\ m^{-1}$)
f_i	Soil texture adjustment parameter
F_{MR}	Motion resistance (kN)
F_{Road}, F_{Field}	Sum of forces on vehicle when on road/field (N)
F_a, F_{grad}, F_{drag}, F_{rr}	Acceleration, gradient, drag and rolling resistance forces (N)
F_N	Normal force (N)
F_D	Draught force (N)
n	Field order number
ICE	Internal combustion engine
m_a	Soil moisture content (mm)
x	Field task
m_p	Soil moisture content at previous time step (mm)
m	Mass (kg)
N_B	Number of additional batteries
N_V	Number of vehicles
N_C	Number of chargers
P_C	Charger power (kW)
P_D	Draft power requirement (kW)
P_{Field}	Total field work power requirement (kW)
P_R	Rated vehicle power (kW)
P_V	Vehicle power (kW)
Q_d	Drainage water flow (mm)
Q_r	Run-off water flow (mm)
Q_e	Evapotranspiration water flow (mm)
S, S_{Road}	Field and road speed ($km\ h^{-1}$)
s	Slippage (decimal)
SoC, θ	State of charge
θ_{min}	Minimum state of charge (decimal)
θ_{max}	Maximum state of charge (decimal)
$\theta(t)$	State of charge at time t (decimal)
t	Simulation time (h)
T_{cc}	Charging time (h)
T_{Field}	Available work time before recharging (h)
T_D	Total active time (d
T_{Spring}	Total active time during spring (d)
v	Vehicle speed ($m\ s^{-1}$)
W	Machine width (m or no. of tools)
X	Fieldwork task
α	Gradient (%)
η_{Field}	Field efficiency factor (decimal)
η_{Motor}, $\eta_{Transmission}$, $\eta_{Battery}$, $\eta_{Charger}$	Efficiency factors (decimal)
ρ_{air}	Density of air ($kg\ m^{-3}$)

lower fuel import dependency (Engström & Lagnelöv, 2018). The benefits are achieved at the expense of lower profitability, since battery electric drives are less compatible with the normal working hours of tractor drivers. This is because the energy storage capacity of batteries is generally too low to support several hours of heavy field work, which would require recharging repeatedly during the working day or choosing a large battery. In a study on a John Deere field tractor, a battery of 130 kWh was not sufficient for an entire working day requiring a 3-h recharge after 4 h of mixed field work (John Deere, 2017). Thus, using a battery electric drive (BED) tractor would lead to a trade-off between a longer working day for the driver or a reduced total field time, so conventional-sized, manned BED tractors are currently not an economically competitive option for field operations.

There are two options to overcome this, autonomous drive and rapid recharging systems. Autonomous drive could enable a similar or higher workload by operating a low-powered vehicle for a larger proportion of the day compared with a conventional, manned tractor. Several autonomous agricultural vehicles currently exist in various stages of development. These range from vehicles based on conventional tractors (Case IH Agriculture, 2019; Oksanen, 2015) to small robots designed for very specific tasks (Fendt, 2017; Young, Kayacan, & Peschel, 2018) and even smaller autonomous implement carriers like Thorvald II (Grimstad & From, 2017), SRFV (Bawden, Ball, Kulk, Perez, & Russell, 2014; Young et al., 2018) and Robotti (AgroIntelli, 2019; Green et al., 2014).

There are currently two main solutions for BEVs to achieve faster, more optimised recharging: conventional plug-in conductive charging (CC) with a high-power contact charger (commonly used with on-road BEVs), or the use of exchangeable battery packs that recharge at lower power. The latter are mainly used in industries where a high vehicle up-time is essential, such as in city-buses or forklifts in depots and warehouses. In a previous study, one such battery exchange system (BES, also called battery-swap system) was shown to replace a city bus battery in 60 s without needing manual assistance (Song & Choi, 2015). Several of the needs match those in agriculture, so the method should theoretically fit in agricultural applications.

The aim of this modelling study was to compare two different battery recharging methods (CC and BES) with regard to active time required, time distribution and energy use for multi-vehicle BED systems. Comparisons with simulated diesel-driven vehicle systems were also made. The model used was a dynamic model designed to simulate a BEV system for agricultural field operations in a Swedish context.

Table 1 – Properties of the model fields. All crops were grown on an equal number of fields. Distances based on the assumption that field work started on fields closest to the farm centre.

Crop	Field size [ha]	Distance field-to-farm [D_F, km]	Field order no. [*n*]
Barley	22, 13, 15	2, 2, 6	3, 4, 11
Oats	10, 26, 14	1, 3, 4	1, 6, 8
Spring wheat	15, 22, 13	3, 5, 6	5, 9, 12
Winter wheat	16, 6, 28	1, 4, 5	2, 7, 10
Total area ha			
Barley	Oats	Spring Wheat	Winter Wheat
50	50	50	50

2. Method

2.1. *Farm and crop system*

A hypothetical cereal farm of 200 ha, located in Uppsala, Sweden, and operated during one growing season, was modelled. The cereal farm was assumed to grow barley, oats, winter wheat and spring wheat, in equal amounts (Table 1). Barley, oats and winter wheat are the most commonly grown cereals in Sweden (Statistics Sweden, 2018), while spring wheat is a normal complementary cereal.

The cropping period was split into three working periods, spring, summer and autumn (Fig. 1). The operations in each working period followed a typical conventional cereal-dominated cropping system in Sweden, with soil cultivation and drilling (in autumn or spring), use of mineral fertilisers, spraying with chemical pesticides and combine harvesting. The necessary field operations were decided by the crop grown on each field according to normal agricultural practices. The intervals between the working periods were designated non-active growing periods in which no operations were required.

The number of days assumed for each period was based on data for Swedish wheat fields (Nilsson, 1976) (Table 2). Dates for the working periods for winter wheat and barley were similar to those described by Myrbeck (1998) for the Uppsala region. The start dates shown in Table 2 were used to trigger the start of operations within each period (i.e. spring, summer, autumn) and the non-active growing periods, when no operations were scheduled and the tractors were inactive. If tasks from the previous period were delayed, they were assumed to be completed before the next period began.

2.2. *Control logic*

A dynamic model was developed using discrete event simulation and state-based logic for decision making. The simulation was performed in MATLAB (R2017b, The MathWorks Inc. (Natick, MA, USA)) and its toolboxes Simulink, StateFlow and SimEvent (versions 9.0). A simplified decision tree for the control logic and the different simulation modules and states is shown in Fig. 2. Sections 2.3-2.7 describe in detail the states and modules, in the order shown in Fig. 2.

The model was run with the list of inputs shown in Table 3. The main variable used to evaluate the results was the total number of active days (T_D), which is the sum of all time spent in the following states: field work, road transport, charging and workability control. It was chosen as it represents a metric of the capacity of the system. In addition, the time when each field operation finished was recorded, as was the amount of time spent in each state and the total energy needed.

2.3. *Vehicle model*

In discrete event simulation, an agent or entity is required. In the present case, the agent was the electric agricultural field

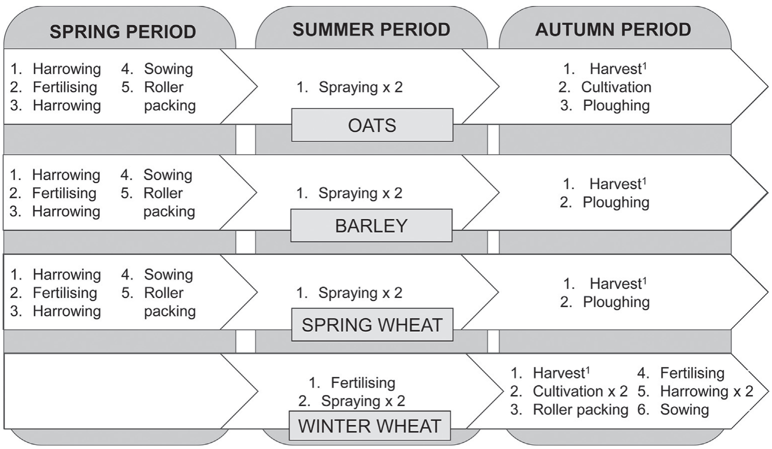

Fig. 1 – Working periods (spring, summer, autumn), crop operations and order of operation in the working periods
[1]Harvesting is not included in the simulation, due to use of a combine harvester instead of tractor as the main vehicle.

Table 2 – Definitions of the different working and non-active periods in the model, and the number of days available for each period.

	Start date	No. of days	Simulation time interval [t, h]
Spring period:	16/3	61	0–1464
Non-active period 1	16/5	30	1465–2184
Summer period	15/6	31	2185–2928
Non-active period 2	16/7	47	2929–4056
Autumn period	1/9	61	4057–5520
Simulation end	1/11	–	5520

tractor, modelled as a general BEV. General variables were used for the agent vehicle, instead of empirical technical data, as the aim was to understand the dynamics and the differences between the different charging methods. The main inputs used to define the vehicle were effective vehicle power (P_V) and rated battery energy content (E_R). In addition, rated vehicle power (P_R) denotes the rated engine power for comparison and effective battery energy content (E_B) denotes the useable fractions after losses of E_R:

$$P_V = P_R\ \eta_{Transmission} \tag{1}$$

$$E_B = E_R\ \eta_{Battery}\ (\theta_{max} - \theta_{min}) \tag{2}$$

where, $\eta_{Transmission}$ and $\eta_{Battery}$ are assumed average decimal efficiency factors. Exact values are given in Table A.1 in an appendix to this paper.

Every battery has a dynamic state–of–charge parameter ($\theta(t)$) that varies dynamically between its minimum (θ_{min}) and maximum value (θ_{max}), indicating the fraction of E_R that remains at any given time. It was the only internal battery variable measured for this study.

To better study a multi-vehicle system of smaller vehicles, P_V was kept constant at 50 kW, which gives the vehicles a P_R of 58.5 kW. A permanent magnet direct current motor (Andersson, 2019) was assumed. Different numbers of identical vehicles (N_V) with the qualities P_V and E_R were then created as simulation agents. To study the autonomy of the vehicles, it was assumed that the BED systems worked autonomously for 24 h d^{-1} and the diesel systems had the option of full 24-h autonomy or 10 h of manned operation.

2.4. *Soil moisture and workability*

Workability is defined by Mueller, Lipiec, Kornecki, and Gebhardt (2011) as the capability of the soil to support tillage. To determine when field operations could be

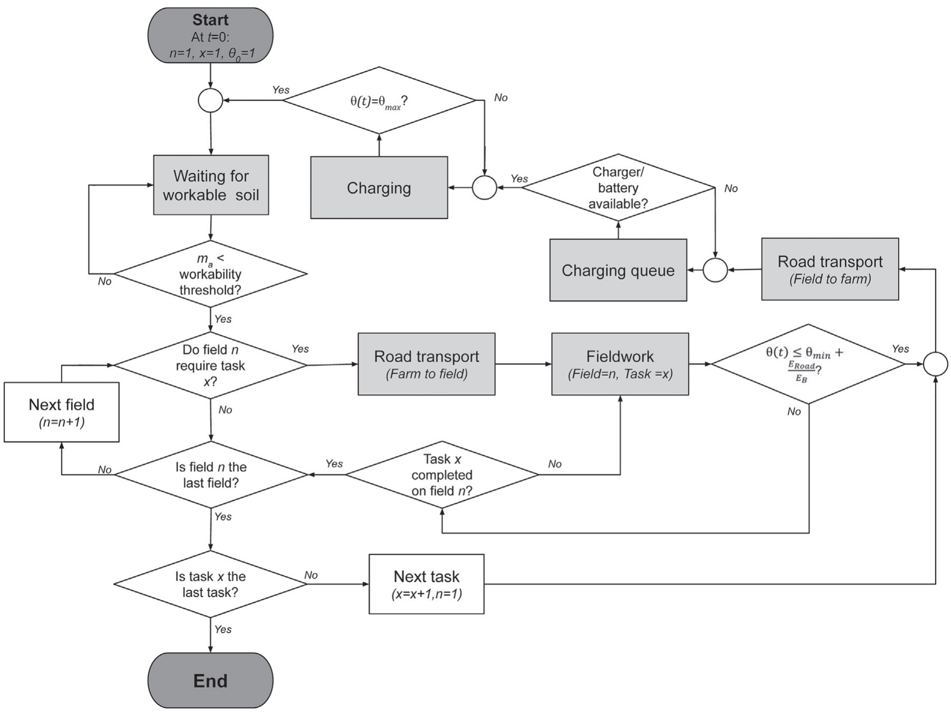

Fig. 2 – Flowchart of the control logic of the vehicle in the simulation. The grey squares represent states and the white diamonds decisions. The dark grey rounded squares represent start and end points, and t, n and x denote time, field number and task number, respectively.

Table 3 – Variable inputs used in the model. Each simulation used a combination of one parameter from each row to define the system configuration. It was assumed that every vehicle had one on-board battery and N_B denotes the number of additional batteries available. For conductive charging (CC), N_B is irrelevant and was not included. The chosen parameters for the base case configurations are shown in bold type.

Input	Range of values
Vehicle power (P_V, kW)	**50**
Charger power (P_C, kW)	10, 25, **50**, 75, 100
Rated battery energy capacity (E_R, kWh)	25, **50**, 75, 100, 150
Yearly weather data	1989–2018
Number of tractors (N_V)	1, **2**, 3, 4, 5
Number of additional batteries (N_B)	**1**, 2, 3,4
Number of chargers (N_C)	**1**, 2, 3

performed, workability based on weather had to be estimated as shown in Fig. 3. The calculated soil moisture level was continuously compared against a threshold for workability taken from de Toro and Hansson (2004). It in turn is based on a value of the field capacity (FC) of clay soils (27.2% or 89.8 mm for a 300 mm soil layer) taken from Witney (1988). A workability threshold of 85% of FC (76.3 mm) was assumed for all general tillage operations except ploughing, for which a threshold of 110% of FC (98.7 mm) was assumed. If the soil moisture content (m_a) was higher than the workability threshold, the vehicle had to wait on the farm until the soil had dried out to below the threshold (Fig. 3). The vehicle then resumed operations. If the vehicle was out in the field, it was assumed to complete its current task before returning to the farm.

In order to calculate soil moisture content, and by extension workability, soil and weather data were needed. The hypothetical Swedish cereal farm was assumed to lie in the production area "Plain districts of Svealand (Ss)" categorised by Myrbeck (1998). The dominant soil type in the region is loamy clay soil with a high clay content (range 25–60%, mainly 40–60%) (Paulsson, Djodjic, Ross, & Hjerpe, 2015). Data on hourly precipitation, monthly mean air temperature and daily number of sunshine hours for the period 1989–2018 were obtained from the Swedish Hydrological and Meteorological Institute (SMHI, 2019). These data derived from different weather stations. A weather station in Uppsala (59.8586, 17.6523) supplied data on precipitation in the periods 1989–2008 and 2013–2018 and on monthly air temperature 1989–2018. As data for some years and some parameters were unavailable from the Uppsala station, other stations nearby were used and similar weather conditions were assumed. A weather station in Enköping (59.6557, 17.1121; 40 km from the Uppsala station) supplied precipitation data for 2009–2012, while a weather station in Stockholm (59.3534, 18.0634; 60 km from the Uppsala station) supplied data on daily number of sunshine hours 2008–2018. Data on number of sunshine hours 1989–2007 were not available from any nearby weather station, so the average value for 2008–2018 was used.

The weather and soil data were used to calculate hourly soil moisture content (m_a) in soils in a temperate climate with the water balance model described by Witney (1988) and Nilsson and Bernesson (2010):

$$m_a = m_p + Q_p - Q_r - Q_d - Q_e \tag{3}$$

where (units mm in all cases): m_p is soil moisture content in the previous time step, Q_p is precipitation, Q_r is surface runoff, Q_d is drainage and Q_e is evapotranspiration, calculated according to Nilsson and Bernesson (2009). This equation is only valid for the top 300 mm of the soil layer and assumes the layer to be uniform.

Values for clay loam and additional values from Witney (1988) were used for Q_p, Q_r, Q_d and Q_e. At the start of the simulation, it was assumed that the soil moisture started at field capacity, due to thawing and early spring precipitation. The validity of the model has been tested by Nilsson and

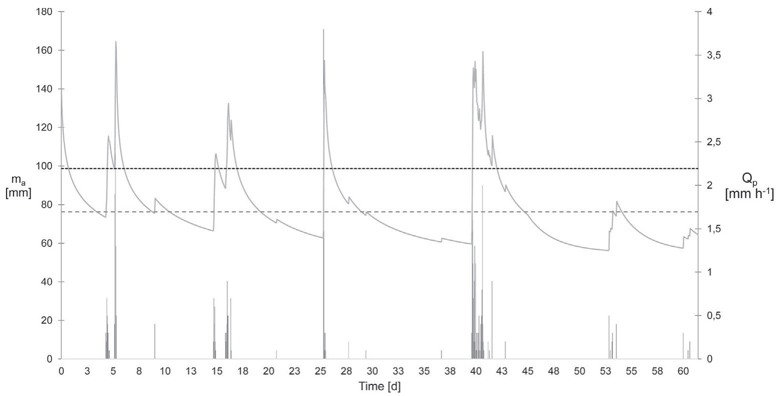

Fig. 3 – Calculated hourly soil moisture content (m_a, solid line) of the top 300 mm soil layer in the spring period (first 61 days of the simulation) using data from 2008. Hourly precipitation (Q_P) is shown as black bars. The workability thresholds for ploughing (black dashed line) and for general tillage (grey dashed line) are also indicated. In 2008, 84% of hours were predicted to be workable for ploughing and 55% for general tillage.

Hansson (2001) against COUP (a hydrological model for soils, previously named SOIL) and found to be adequate.

2.5. Road transport

Each field was assigned a distance from the farm, along with other field parameters (see Table 1). It was assumed that the field operations were executed in order of distance from the farm, starting with the field closest to the farm, represented in the model by the field order number, n.

2.5.1. Vehicle dynamics

Calculations of vehicle dynamics were made for the forces acting upon the vehicle on the road (F_{Road}). Rolling resistance, drag force, grading force and acceleration force for road transport were calculated continuously, using equations and constants from Reif and Dietsche (2014):

$$F_{Road} = \Sigma F = F_a + F_{grad} + F_{drag} + F_{rr} \tag{4}$$

$$F_a = m\,a \tag{5}$$

$$F_{grad} = F_N \sin(\alpha) \tag{6}$$

$$F_{drag} = \frac{1}{2}\rho_{air} v^2 C_D A \tag{7}$$

$$F_{rr} = F_N\, C_{rr} \tag{8}$$

where (all in N): F_a is acceleration force, m is vehicle mass in kg, a is acceleration in m s^{-2}, F_{grad} is grading force, F_N is the normal force, α is the gradient or incline angle in degrees (°), F_{drag} is the drag force, ρ_{air} is the density of air in kg m^{-3}, v is the vehicle's speed relative to the air in m s^{-1}, C_D is drag coefficient, A is the frontal area of the vehicle in m^2, F_{rr} is the rolling resistance force and C_{rr} is the rolling resistance coefficient.

The driveline was designed to have peak power and handle accelerations up to 2 m s^{-2} or gradients of up to 10%.

Every road transport event had the following phases: an 1-min acceleration phase where the road speed increased from 0 to 35 km h^{-1} with a maximum acceleration of 2 m s^{-2}, a 1-min deceleration phase where the speed decreased from 35 to 0 km h^{-1} and a remaining time when the vehicle was assumed to travel with an average speed of 35 km h^{-1}, as also assumed in Engström and Lagnelöv (2018) and Engström et al. (2015). The acceleration and deceleration phases included all decelerations and accelerations made during the trip. The resulting total average speed was denoted S_{Road} and expressed in km h^{-1}.

2.6. Fieldwork and operations

The force (F_{Field}) and power (P_{Field}) requirements for field work were based on the vehicle dynamics (Eqs. 4, 5, 6 and 8), with an added factor for the force exerted by the implement (F_D) as shown in Eq. (10). In addition, appropriate values for rolling resistance on clay soil and on-field vehicle speed were used. For exact values, see Table A.1.

The value of F_D was determined for each of the operations in Fig. 1, using empirical implement draft equations and the inherent motion resistance, calculated for firm clay soil based on ASAE (2000):

$$P_{Field}(x) = F_{Field}(x)\; v;\; P_{Field}(x) \le P_V \tag{9}$$

$$F_{Field}(x) = \Sigma F = F_a + F_{grad} + F_{drag} + F_{rr} + F_D(x) \tag{10}$$

$$F_D(x) = (A(x) + B(x)\,S + C(x)\,S^2)\; f_i\; W(x)\; 100\; D_T(x) + F_{MR} \tag{11}$$

$$F_{MR} = F_N \frac{\left(\frac{1}{B_n} + 0.04 + \frac{0.05\,s}{\sqrt{B_n}}\right)}{1000} \tag{12}$$

where $F_D(x)$ is draft force requirement for field work task x, $P_{Field}(x)$ is total power requirement for task x, f_i is a dimensionless soil texture adjustment parameter, A, B and C are machine parameters, v is the vehicle's speed in m s^{-1}, S is field speed in km h^{-1}, W is implement width for task x in m (or in no. of tools), D_T is tillage depth in m, F_{MR} is motion resistance in kN, s is decimal slippage and B_n is a dimensionless ratio depending on wheel parameters and soil type.

Five of the seven field operations were calculated using this method. The other two, fertiliser spreading and pesticide spraying, were calculated using empirical data taken from Lindgren, Pettersson, Hansson, and Norén (2002), who measured the power requirements for different operations by multiple tractors in the field during a growing season. Spraying was not measured in that study, so measured values for spraying recycled urine under good conditions were used in the model instead. Empirical values for ploughing, cultivation, sowing, roller packing and harrowing taken from Lindgren et al. (2002) were also used to validate the model (Fig. 4). It was assumed that the battery would always need recharging before any spraying tank or fertiliser bin was empty and that tank/bins were refilled on the farm while the battery was recharging or being replaced, and therefore no separate modelling was needed.

The rate at which the tractor could perform each operation was calculated according to Witney (1988):

$$C_o(x) = \frac{W(x) S \eta_{Field}}{10} \tag{13}$$

where C_o is the overall rate of work for task x in ha h^{-1}, η_{Field} is a decimal field efficiency factor due to sub-optimal field geometry and implement width, and 1/10 is a conversion unit for km m h^{-1} to ha h^{-1}. All calculated C_o values are shown in Table A.2.

The tractor remained in the field until the current task was completed or the battery energy reached a pre-set threshold of the sum of θ_{min} and the additional energy needed for transport back to the farm. When one of these was triggered, the vehicle returned to the farm for recharging and to prepare for the next field or operation. If the tractor left the field with more battery energy than the threshold, this resulted in a correspondingly shorter charging time, as described in section 2.7.1. The behaviour of the battery during work in field n and the thresholds for exiting can be described as follows:

$$\theta(t) = \theta(t_0) - \frac{P_{Field}}{E_B} t;\quad \theta_{min} + \frac{E_{Road}(n)}{E_B} \le \theta(t) \le \theta_{max} \tag{14}$$

where t_0 denotes the simulation time (h) when field work started.

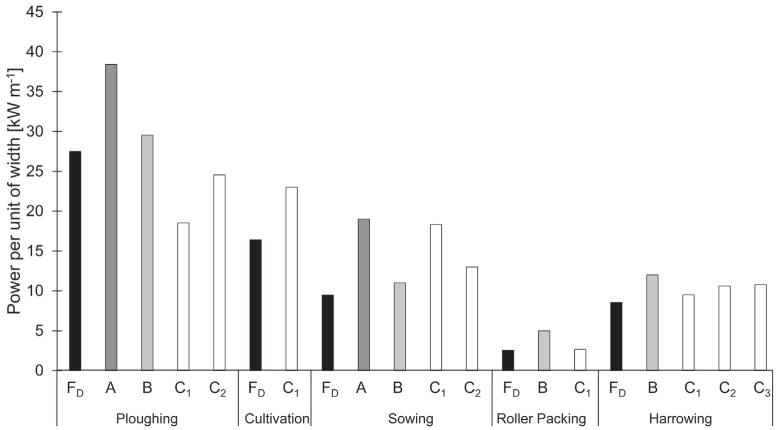

Fig. 4 – Comparison of calculated draft power requirement based on ASAE (2000) and measured values (Lindgren et al., 2002). Draught force (F_D) is the calculated value used in the model, other bars represent measured values for different tractor models: Case 240 IH Max (A), Valtra 6650 (B) and Valtra 6600 (C_i).

2.7. *Charging system and battery*

2.7.1. *Charging system modelling*

The BEV was assumed to use one of two charging methods; conductive charging (CC) as described in Yilmaz and Krein (2013), or a battery exchange system (BES) where the entire battery pack is replaced, as described in Cheng, Chang, Lin, and Singh (2013) and Kim, Song, and Choi (2015). When the battery was replaced in the BES, the empty battery was assumed to be recharged with CC while the tractor returned to work with a fully charged battery pack, meaning that the BES still needed a CC system. The time required for replacement of a battery pack was set to a constant 10 min. Shorter changing times have been reported for cars by Tesla and Better Place (Adegbohun, von Jouanne, & Lee, 2019; Afonseca, 2018) and times down to 60 s for large battery packs in buses (Kim et al., 2015). Here, a higher changing time was set to give a margin of error.

For the CC system, the vehicle acquired a resource labelled *charger* (of the N_C available) in the model and then proceeded to charge up to the threshold shown in Equation (15). If no charger was available, the vehicle was placed in a queue until a charger was available. When a battery was fully charged, it released its charger for further use. The BES was modelled in a similar way to the mixed queue network used by Tan, Sun, Wu, and Tsang (2018), also using multiple coupled queues for different resources (vehicles, batteries etc.). In the present model, the vehicle first acquired a fully charged battery in the form of a resource labelled *battery* (of the N_B available) and waited the fixed battery replacement time before exiting fully charged. The empty battery acquired a *charger* resource and charged via CC, and when this was done the battery resource was made available for the next vehicle as a fully charged battery.

The process of CC battery recharging can be approximated by a linear increase in SoC over time. This linear method can be an adequate fit for some methods of charging at certain intervals of SoC, in this study for the CC/CV method (constant current/constant voltage (CC/CV), as described by Shen, Tu Vo, and Kapoor (2012)), for SoC between 0.2 and 1. This has been used in calculations and modelling in several studies (Hamidi, Ionel, & Nasiri, 2015; Harighi, Bayindir, & Hossain, 2018; Klein et al., 2011).

The simulated behaviour of $\theta(t)$ during charging via CC can be described as follows:

$$\theta(t) = \theta(t_0) + \frac{P_c\ \eta_{charger}}{E_B} t;\ \ \theta_{min} \le \theta(t) \le \theta_{max} \tag{15}$$

The tractor remained at the charger until $\theta(t)$ was equal to θ_{max}. The tractor was then released. Both of the recharging methods, CC and BES, in the BED system were simulated to take place on the main farm.

2.7.2. *Battery modelling*

As the focus of the simulation was to identify general relationships and patterns, the battery was modelled as an internal system with the function of an energy reservoir. The dynamic SoC-level, $\theta(t)$, was the only internal battery variable that varied dynamically during the simulation, even though energy use was also measured. Use of $\theta(t)$ as the only state-variable in simplified battery models has been described previously, by e.g. Tremblay, Dessaint, and Dekkiche (2007) and Grunditz and Thiringer (2016). The battery had a set restriction where the SoC-level could not go below θ_{min}, to avoid deep discharge damage and ensure adequate operational life time. To achieve this, how much energy would need to be reserved for transportation to and from the field (E_{Road}) was predicted. The remaining part of the battery energy was used for field work (Fig. 5).

For CC, the battery was modelled as using a simplified method for discharging where $\theta(t)$ decreases linearly with time. It was assumed that the battery was able to receive charging power and power the motor without constraints, regardless of size. It was also assumed that the battery was

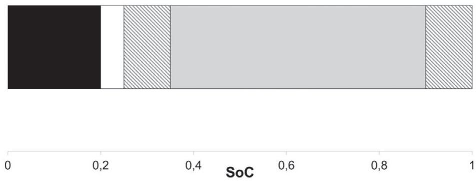

Fig. 5 – Example of state of charge (θ) distribution of the modelled battery in: field work (grey), road transport (diagonal), θ_{min} (black) and losses due to non-perfect efficiency (white).

new and unused at the start of the simulation. Battery deterioration and resulting loss of capacity was omitted from the model, even though it is of great interest and it should be included in future studies.

2.8. Diesel system

To make comparisons against conventional agricultural vehicle systems, the model was modified to simulate diesel tractors with the same vehicle power (P_V) and number of vehicles (N_V) as the simulated BEVs. Two cases were simulated; an autonomous diesel tractor operating 24 h d^{-1} and a diesel tractor operating for 10 h d^{-1}, the latter simulating a conventional manned vehicle. The 10-h version was constrained to never work more than 10 h d^{-1}, but could start at different times of the day, depending on the weather.

The main differences were replacing the battery with a diesel tank and the charger with a diesel pump, and changing the engine efficiency to match ICE levels. Data on diesel tank volume were for the CLAAS ATOS (55–79 kW) series of tractors (CLAAS, 2018). The diesel tank was assumed to carry 130 l of diesel, corresponding to a battery of 1315 kWh, which was used as E_R for the diesel systems as it was assumed that no losses occurred in the tank and that all diesel was used. The electric charging was replaced with a diesel pump with a flow rate of 50 l [diesel] min^{-1}. This corresponds to the energy flow in an electric charger of 30.3 MW, which was used as P_C for the diesel systems. It would give a refuelling time of <3 min, which made having more than one fuel pump redundant, so N_C was set to 1. The engine efficiency of combustion engines is non-constant in real use, but in this simulation it was set to a constant 30%, which corresponds to an average to high value for smaller agricultural tractors (Wasilewski et al., 2017).

2.9. Simulation inputs and base case configuration

A base case configuration was chosen as a basis for comparison, with the criterion that the resulting mean time needed for field work in the spring period (T_{Spring}) should be roughly 30 days or less for the 30-year period 1989–2018. In the model, the spring period is the most time-consuming and time-sensitive period. It is also of high importance for the remaining cropping period. Multiple configurations could

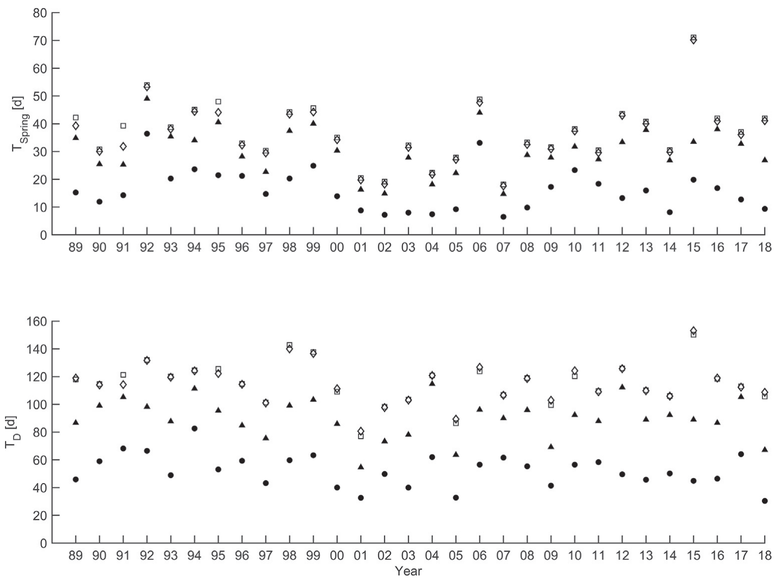

Fig. 6 – Distribution of total active time (T_D) and total active time during spring (T_{Spring}) for the base case configuration over 30 individual years, compared with the corresponding configuration for a battery exchange system (BES). T_{Spring} is calculated from the first workable hour of the spring period, not from the simulation start. Conductive charging (CC) (□), BES (◊) and diesel systems with 24-h (•) and 10-h (▲) working periods are shown.

Table 4 – Average value, median and standard deviation for total active time (T_D) and total active time during spring (T_{Spring}) for the base case configurations (see Table 3) in two battery electric drive (BED) systems (conductive charging (CC), battery exchange system (BES)) and two diesel tractor systems with different work periods (10 or 24 h d^{-1}), 30-year sample size.

	T_D				T_{Spring}			
	CC	BES	Diesel (10)	Diesel (24)	CC	BES	Diesel (10)	Diesel (24)
Average	115.2	115.4	89.7	52.3	37.2	35.0	30.2	16.1
Median	116.4	114.3	89.5	51.7	37.6	35.1	29.5	15.0
Std. Dev.	15.1	14.9	14.3	11.5	10.9	10.7	8.3	7.3

meet this criterion, but the base configurations shown in Table 3 were chosen as they were compatible with the aim of the study by allowing multi-vehicle system dynamics to be considered. Both modes of recharging in the BED systems were simulated using the base case configuration. In addition, the diesel systems were simulated for comparison with the same inputs; apart from P_C and E_R as described in section 2.8. The different inputs were chosen as they all represented different solutions that exists on the market today or have been studied previously. Furthermore, they were chosen to be reasonable for the economy and fuse size of a farm of the given size.

3. Results

3.1. *Base case configuration results*

Simulating the base case scenario for 30 different years (1989–2018) gave the T_{Spring} and T_D values shown in Fig. 6 for CC, BES, diesel with a 10-h working day and diesel with a 24-h working day.

The difference between years was significant and reflects weather dependency, as only the weather data varied between the years. Using BES always resulted in lower T_D and T_{Spring} than using CC for this configuration (Fig. 6), although the difference was small. For the spring period, the 10-h diesel system had shorter T_{Spring} than both the BES and CC systems, with a median value of 3.8 d. When considering the entire year, the 10-h diesel system had consistently shorter T_D than the BED systems, because of the more demanding field work done in autumn (ploughing and power cultivation). The average and median values for the entire 30-year period are shown in Table 4.

Compared with CC, the average T_D with BES was 0.2 d longer, while T_{Spring} was 2.2 d shorter. However, the median values showed that BES was 2.5 and 2.1 days shorter for T_{Spring} and T_D, respectively. The 24-h diesel system resulted in the shortest average T_D, 52.3 d. With the 10-h diesel system, T_D increased to 89.7d. The average time distribution for the different base cases is shown in Fig. 7. Apart from different T_D, a shift in the distribution was also noted between the cases.

The average time spent on road transport per vehicle was similar between the two modes of recharging in BED systems (11.6 d for BES and 12.1 d for CC). This was unsurprising, as the

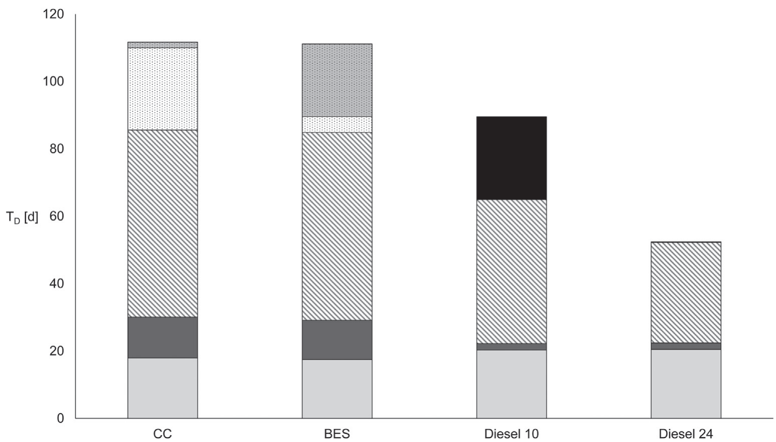

Fig. 7 – Average time distribution per vehicle for the base case for different charging methods (battery exchange system (BES), conductive charging (CC)) and for two diesel systems with different work periods (10 and 24 h). Charge (white dotted) denotes all types of refuelling, charge queue (grey dotted) is the time spent queuing for refuelling, weather (white diagonal) is the time spent waiting for improved soil workability, transport (dark grey) is the time spent in transit between farm and field, and field work (light grey) is the time spent doing field work. For the 10-h diesel system, rest (black) denotes the time outside the working schedule of a driver.

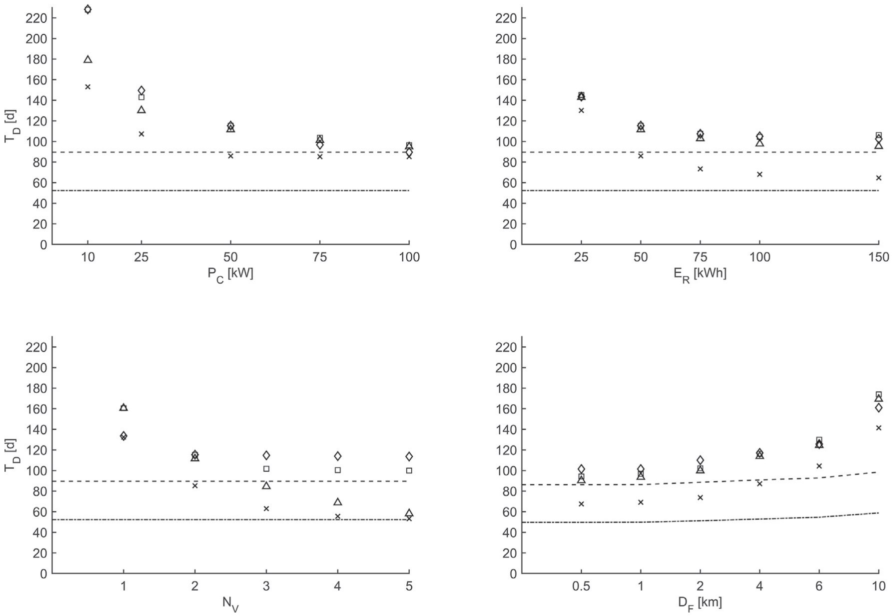

Fig. 8 – Change in total active time (T_D) in response to changes in: charger power (P_C, top left), battery energy content (E_R, top right) and number of vehicles (N_V, bottom left), with all other parameters set to the base case configuration ($N_V = 2$, $N_C = 1$, $N_B = 1$, $E_B = 50$ kW h, $P_C = 50$ kW). Variable distance from field to farm (D_F, bottom right) is also shown for all cases. CC (□) = conductive charging, BES (◇) = battery exchange system. CC*(Δ) and BES* (X) are configurations with no or minimal charging queues, for comparison with a better optimised system. The two diesel systems, 10-h (dash-dotted line) and 24-h (dashed line), with $N_V = 2$, are also displayed for comparison.

time in transit depended on the number of times recharging was required. This in turn depended on the battery capacity, which was equal between the modes. Since the time spent refuelling and in transit was dependent on the energy carried by the vehicle, the two diesel systems spent a low fraction of their time on both, 1.95–1.96 d vehicle^{-1}. The amount of time spent working was roughly equal between the cases (17.5–20.5 d vehicle^{-1}, 35.0–40.9 d total), as a certain amount of fixed work was needed to complete all tasks, but the fraction of total time spent on field work varied greatly, from 16% for BES to 39% for the 24-h diesel system. The BED systems spent slightly less time working in the field due to their higher driveline efficiency compared with the diesel systems. The time spent waiting for acceptable weather, and by extension field workability, was a large fraction (48–57%) of the total time for all systems. The time spent waiting for acceptable weather varied between the systems, from 29.8 to 55.7 d, but the fraction was similar in all cases.

Comparing CC and BES, the main difference was in the time spent charging. The time saved on charging for BES constituted the difference in T_D between the systems. Optimising the BES configuration to avoid charging queues could give a further 19.9 d reduction compared with CC, as queueing took up 82% of the total time spent recharging for the BES. Although N_C and P_C were equal between the modes, BES had a larger queue time fraction than CC, implying a scheduling problem with charging, i.e. greater risk of multiple vehicles returning for recharging at the same time, creating queues.

It is important to note that, even though the states are mutually exclusive, time spent in one can reduce the time spent in another, see Fig. 7. For example, time spent charging in the CC system could be time that would otherwise be spent waiting for better weather, or in the 10-h diesel system the workability control comes before the daily working time control, meaning that time spent waiting for better workability would otherwise have been spent waiting for the working day to begin.

3.2. *Variable input influence*

In addition to the base case, simulations were run with the inputs shown in Table 3 and where P_C, E_R and N_V were all varied from the base case separately, for both recharging systems and both diesel systems (Fig. 8). For the BED systems, both the series with the base case configurations and more optimal systems in terms of N_B and N_C were included.

Charger power (P_C) was influential for both CC and BES, decreasing T_D when increased to 75 kW where the number of chargers could successfully service all vehicles. Further increases gave only a limited effect. For the optimised BES, a maximum P_C of 50 kW sufficed, provided enough chargers and batteries were available. For $P_C < 50$ kW, CC had a lower T_D compared with BES, while BES had lower T_D in every other case.

Rated battery energy content (E_R) had a similar effect on both systems, with a decrease in T_D with increased E_R, and subsequently E_B. For CC, this was characterised as a diminishing return, since a larger E_R meant more fieldwork before recharging, but also longer charging times that counteracted the gains. This is evident in Fig. 8, where the optimised CC system was only slightly better than the base case for all battery sizes. Further gains required an increase in P_C in addition to increases in E_R to keep the charging time low. For BES the benefits were more direct, as a large E_R did not necessarily correlate with a longer charging time. As long as a fully charged battery was available when the tractor returned for recharging, a larger E_R simply meant more time for field work. This is seen in the large difference between the base case configuration and the optimised system for BES in Fig. 8.

Increasing N_V led to lower T_D, especially for the optimised systems. $N_V > 2$ led to T_D that was lower than for the manned diesel system, and a higher number of vehicles could compete with the unmanned diesel system. The distance between farm and field (D_F) was also varied, as can be seen in Fig. 8. For the diesel systems this parameter had a low impact on T_D, with a difference of 9.2–12.2 d between $D_F = 0.5$ and $D_F = 10$ km. In comparison the T_D of both CC systems and the non-optimised BES was highly impacted by an increase in D_F, with an increase of 73.8–79.6 d when D_F increased from 0.5 to 10 km. An optimised BES was less affected and showed an increase of 59.6 d under the same inputs. For $D_F > 4$ km, both BES performed better than their CC counterparts.

The results of varying number of chargers (N_C) for different P_C and E_R of the CC system are shown in Fig. 9. An increase in N_C gave a benefit in terms of lowered T_D until elimination of queues, after which a further increase gave minimal benefit. As can be seen in Fig. 9, an increase in N_C was most effective with lower charger capacities, while at higher P_C an increase yielded no improvement, as the charger need was already met by faster chargers. While N_C affected T_D for different battery sizes, the effect was less pronounced than that of charger power.

For the BES, some notable patterns emerged, as shown in Fig. 10. Increasing P_C, N_B or N_C was only beneficial up to the point where queues and general waiting time could be avoided. Increases beyond that point had no or minimal benefit on T_D, most notably seen at $N_B \geq 2$ (Fig. 10). Similar findings were obtained for other configurations of the BES.

3.3. *Energy and time consumption*

Energy consumption for the different base cases was measured and compared with that in other studies on similar crops and environments (Daalgard, Halberg, & Porter, 2001; Kitani et al., 1999; Chaston, 2008; Lindgren et al., 2002; Safa, Samarasinghe, & Mohssen, 2010; Wells, 2001; Witney, 1988). Fuel consumption data for field operations from these sources were used in calculations for the spring wheat rotation shown in Fig. 11, where simulated energy use is converted to equivalent litres of diesel. This was done using a density of 845 kg m^{-3} and a net calorific value of 43.1 MJ kg^{-1} was taken from Reif and Dietsche (2014) which is in accordance with the European Union standard for diesel fuels, EN 590. The simulated energy use was obtained through the following equation of energy as a function of the integrated sum of powers for each vehicle N_i and task x:

$$E = \int_0^t \frac{\sum P(N_i, x)}{\eta_{Motor}\ \eta_{Transmission}} dt \qquad (16)$$

where η_{Motor} is the decimal average motor efficiency.

The results showed that the energy consumption for the BED systems was 58.0% lower than for the corresponding

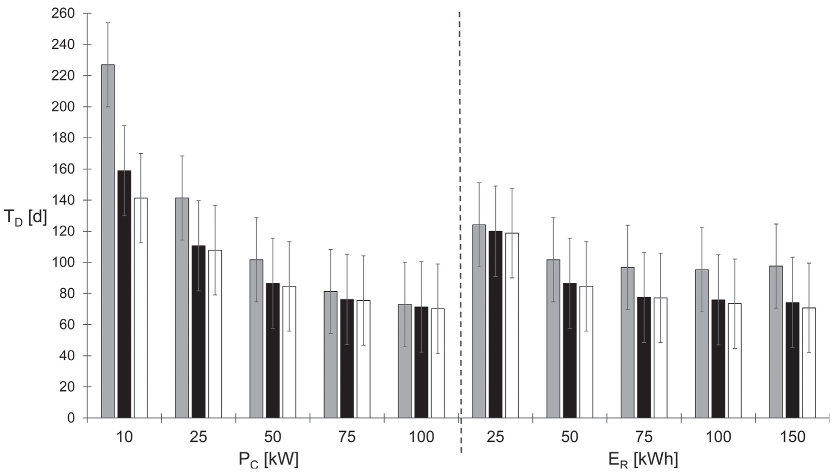

Fig. 9 – Total active time (T_D) for different configurations where number of vehicles, $N_V = 3$ for conductive charging (CC) and charger power (P_C, left) and battery energy content (E_R, right) are varied. All values are 30-year averages, error bars show 2 SDs. On the left $E_R = 50$ kW h and on the right $P_C = 50$ kW. Number of chargers (N_C) 1 (grey), 2 (black) and 3 (white).

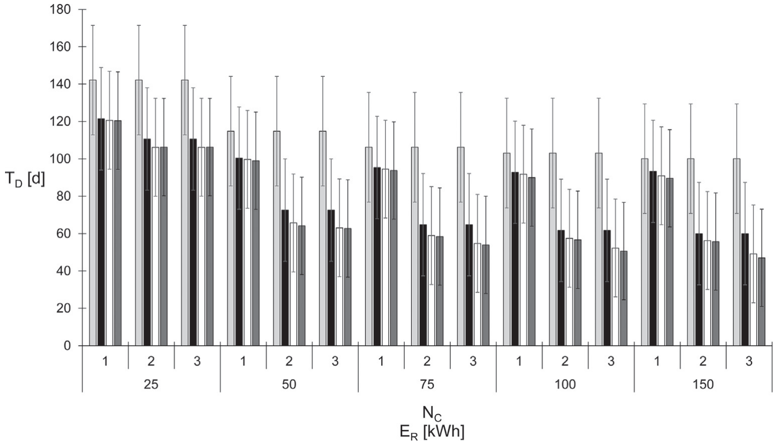

Fig. 10 – Total active time (T_D) for different configurations of number of additional batteries (N_B, columns), number of chargers (N_C, top x-axis) and battery energy content (E_R, bottom x-axis) in the sub-set for the battery exchange system (BES) where number of vehicles $N_V = 3$ and charger power $P_C = 50$ kW. All values are 30-year averages, error bars show 2 SDs. The columns show number of batteries $N_B = 1$ (light grey), 2 (black), 3 (white) and 4 (dark grey).

simulated diesel systems' and 45.8% lower than average empirical values presented previously for similar soil type and weather conditions (Lindgren et al., 2002).

The total time required for each hectare was measured for all cases by normalising the time spent doing fieldwork and transport, in hours, over the total area. For the base case, CC had an average time requirement of 7.8 h ha^{-1} and BES a requirement of 7.7 h ha^{-1}. The time requirement for the diesel systems with 10 and 24 h working time was 5.3 ha^{-1} in both cases.

4. Discussion

4.1. *General results*

There was a non-negligible difference between BES and CC in terms of active time, with BES resulting in lower T_{Spring} and T_D in the majority of years for the base case configurations. In addition, a well-optimised BES was consistently as good as, or

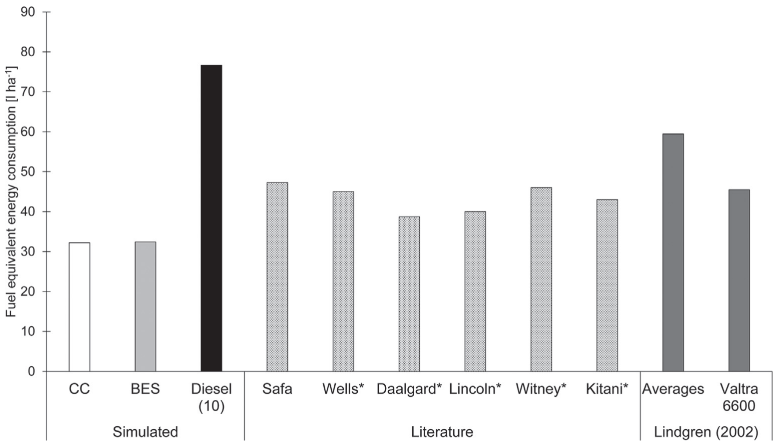

Fig. 11 – Fuel consumption per hectare for a spring wheat cropping system. Comparative values from literature sources on consumption for specific operations and the 30-year average simulated base cases for battery exchange system (BES), conductive charging (CC) and diesel (10-h day). Road transport was not included in the literature sources and data on roller packing were missing from the marked sources (*), so these were omitted from the calculations. Fuel consumption during harvesting was omitted in all cases.

better than, a corresponding CC-system for all configurations. Since the aim of the study was to compare the different charging methods with each other and equivalent diesel systems, the choice of T_D and T_{Spring} were deemed adequate as an indication of which system performed better. In further studies, more in-depth comparisons featuring scheduling, timeliness and time management optimisation are encouraged as they fell outside the scope of this study.

For CC systems, increasing N_C was only relevant when there was a queue to the chargers, which only occurred when low P_C was paired with high E_B. Increasing P_C had less of a diminishing return than increasing E_B, since larger battery capacity meant longer field work runs, but also longer charging times, while increased P_C only yielded shorter charging times. An increase in P_C always yielded a greater improvement in T_D than adding more chargers (i.e. one 50 kW charger resulted in lower T_D than two 25 kW chargers, even though the total charging capacity was the same). This indicates that for CC, few large chargers were better than multiple less powerful chargers. The BES was more flexible and there was no definitive better option. This is best shown in Fig. 8, where a well optimised BES with $P_C = 50$ kW had a lower T_D than the corresponding CC system with $P_C = 100$ kW. For CC, periods of time spent charging coincided with bad weather where the tractor would be unable to work regardless, thereby mitigating the disadvantage of longer charging time compared with BES.

For BES, increasing P_C was only efficient up to the point where queues to a fully charged battery were eliminated, after which no further advantage was gained from increasing the available power. This is similar to the dynamics found by Tan et al. (2018) in their simulation of a BES, particularly for variables N_B and N_C. In contrast, for the CC system larger P_C always proved beneficial, albeit with diminishing returns. For BES, larger batteries proved increasingly beneficial up to the point where the chargers could not provide fast enough charging to avoid queues. Furthermore, after increasing the battery capacity to a high enough level to complete any task in any field, any further benefit was lost as the vehicle was assumed to return to the farm after each field. However, this is a constraint of the simulation and real-world use would derive greater utility from such a battery. The BES also had a flat battery changing time of 10 min on top of the time it took to charge the batteries, which can explain why, for lower D_F, BES had a higher T_D than CC. In most other scenarios this time was small compared with the charging time of the CC system, which resulted in BES being the faster system in those cases.

Increasing the number of vehicles correlated directly with an increase in rate of work (C_o) and was an efficient way of reducing T_D, although again with diminishing returns. For both CC and BES, it was important to increase other variables along with the number of vehicles, as charger capacity and battery availability quickly became bottlenecks and further increases in vehicle numbers yielded no benefits (see Fig. 8). The behaviour of the BED systems with increasing D_F indicates that, due to the frequent recharging of battery systems, they are better suited to an environment where recharging infrastructure is as close as possible, to minimise transport time. For $D_F > 4$ km, both non-optimised BED systems had difficulties completing all operations, especially as heavy tillage required frequent recharging due to the heavy nature of the work. For BES the possibility of bringing multiple batteries to the field exists, and $D_F = 0.5$ km gives a good indication of the optimal benefits of this solution, even though this option was not explored in the present study. The results indicate that it could be a feasible option for fields far away from recharging infrastructure, provided that battery exchange can be facilitated on-site.

The modelled system assumed a heavy tillage cropping system on clay-rich soil in a wet temperate climate, which is energy-intensive and demanding on BED vehicles. This study modelled and simulated a conventional cereal system, with the assumption that BEDs would replace ICE tractors for every activity, without altering the tasks or crops. A simplified and static vehicle model was also assumed. The values obtained for fuel consumption and work rate were similar to those found in other sources, but further research and simulations of vehicles, other environments, soils and cropping systems, and more detailed simulations of vehicles could improve understanding of the benefits and restrictions of these kinds of systems. Ideally, field tests would be a good complement.

4.2. *Workability and weather*

Weather was highly influential, with on average 50.7% of the active time of the year spent waiting for better workability in fields. In this study, no account was taken of the relationship between vehicle weight and workability. Smaller, often lighter, machines were considered and they would probably have a larger window of workability than larger machines. The limit for trafficability (defined as the capability to support agricultural traffic and not harm the soil or ecosystem), and the potential gains from reduced soil compaction were also omitted from the analysis, even though these are arguably among the greatest advantages of smaller vehicles. Further research is required in this area.

In the model, it was assumed that all fields were uniform and identical as regards soil parameters and soil type. This is a simplification, as these parameters can vary between neighbouring fields and even within fields. Hydraulic conductivity in particular is known to vary in-field (Nilsson, Larsolle, Nordh, & Hansson, 2017), but was assumed here to be constant and uniform, following Witney (1988). As weather and soil workability was not the main focus of the study, this simplification could be acceptable. Another assumption was that the control for the workability criterion was made on the farm and, if met, the vehicle completed a run before returning. However, the difference between the simulated fraction of time spent queueing for better workability and the calculated fraction of time when the soil was too moist to be workable was generally small (+/−5% of the time spent waiting in an average year), which indicates that this assumption had a limited impact on the results.

The predicted workability for a certain period was estimated for time steps greater than 1 h. Both de Toro and Hansson (2004) and Nilsson and Bernesson, (2009) predicted workability for a certain day and Witney (1988) suggested predicting the number of working days per month or quarter. Increasing the resolution to hours might lead to a harsher assessment of workability. Daily variations in temperature or moisture (night–day cycle and dew accumulation) were not implicitly included in the model, which for a resolution of days might be accurate but for a resolution of hours might be a simplification. The proportion of time appropriate for field work reported in different studies varies, with most citing 55–70% (de Toro & Hansson, 2004; Nilsson, 1976; Witney, 1988). In this study, the value was on average 48%. A value more consistent with the literature might have been more lenient towards BED systems, as weather was the greatest cause of non-productive time. Apart from the weather in the different years, changing the workability criterion would have had a noticeable impact on the amount of time spent waiting for better workability status. A more lenient criterion would have permitted a larger number of feasible configurations.

4.3. Fixed power and scalability

The power of the vehicle was kept fixed in simulations, as the focus was the charging systems and the general dynamic relationship between BEV and autonomous vehicles. Larger, or smaller, vehicle power would have a noticeable effect that would vary with different mode of use and for different farms, but was not simulated here. The complexity of encompassing all field work operations leads to a problem of optimisation and this article chose to focus on smaller vehicles than the current diesel tractors. Other vehicle concepts such as Thorvald II (Grimstad & From, 2017) solve this by being modular, while the Fendt Xaver (Fendt, 2017) and the TERRA-MEPP (Young et al., 2018) are small, specialist vehicles of lower complexity than an all-operation vehicle and they avoid heavy tilling operations altogether. In future studies, a "ploughing-free" or "no-till" work cycle would be interesting to investigate, as BED systems could be assumed to fit better there than in a conventional work cycle including heavy tillage.

Scalability of the systems is an area of interest for future studies. Systems of the kind studied here might not be used primarily on farms of moderate size, but on larger farms with greater ability to invest in new technology and a greater need for hired manpower. Logistics is a greater bottleneck for farms with large field area and long transport distances than for farms with smaller field area (Engström et al., 2015). In previous studies, field size and shape (Nilsson, Rosenqvist, & Bernesson, 2014), road transport distances (Engström et al., 2015) and total field area have been described as important parameters. Thus analysis of other total field sizes, layout, motive powers and total farm area would be interesting in future research.

5. Conclusions

Dynamic simulation results indicated that autonomous BEV in both BES and CC systems could be similar to conventional manned diesel tractors of corresponding sizes in terms of yearly active days required. This was shown for battery energies significantly smaller than the contents of a diesel tank and at charger powers that are feasible for the fuse size of small-medium Swedish farms, with the lower work rate and less on-board energy of BEDs being offset by autonomous operation. It was also shown that the simulated BED systems had lower energy consumption per hectare than the simulated diesel systems (58% lower) and literature values for diesel systems (17–46% lower).

In base configuration simulations, spring operations were completed in 37.2 d on average for CC and 35.0 d for BES; an improvement of 2.2 d. The average total active yearly time required was 115.2 d for CC and 115.4 d for BES in the base case, while the average values for well-optimised systems showed that BES was 25.7 d faster than CC ($T_{D(CC*)} = 111.6$ d, $T_{D(BES*)} = 85.9$ days) and the manned diesel system ($T_{D(Diesel10)} = 89.7$ d). Choosing BES over CC for similar configurations lowered the required time in all cases except for $P_C < 50$ kW. When multiple chargers or batteries were available, BES consistently performed better than CC. These results indicate that the BES simulated performed better than the CC system on average and as an optimised system. The number of calendar days needed to conduct the necessary work varied asymptotically with component size (i.e. charger power, battery capacity; see Fig. 8). As long as the capacity was enough to avoid bottlenecks, adding extra capacity provided limited improvement. However, when the component sizes were too low, the number of calendar days increased rapidly.

The difference in total active time between the BES and CC systems was small for most of the configurations compared, but BES consistently needed the same or less time to complete all operations than similar CC systems. For both systems, charging queues proved detrimental. As both BED systems generally had a lower rate of work due to frequent recharging than conventional diesel systems, it was important to maximise the time available for field work. Due to the frequent recharging and lower recharging speed, the BED systems spent more time in transit and recharging than the diesel systems, meaning the BED tractors are better suited for farms with their fields nearby. It proved important with a good understanding of the sources of non-productive time. The non-productive time could be reduced by reducing queueing through increasing the battery capacity (providing a longer time between recharges), increasing the charger capacity (decreasing the charging time), scheduling the vehicles to avoid queues, or using non-productive time (mainly waiting for better workability) to charge the vehicle batteries.

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

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Appendix A. Parameter Values and Constants

Table A.1 – Model constants and values used in simulations

Parameter	Description	Value	Source
A	Vehicle front area (m^2)	2	
a	Acceleration ($m\ s^{-2}$)	2	
B_n	Machine/soil ratio parameter	55	ASAE (2000)
C_D	Drag coefficient (decimal)	0.9	Reif and Dietsche (2014)
C_{rr}	Rolling resistance coefficients (decimal)	0.1 (field)	(Witney, 1988)
		0.1 (road)	Reif and Dietsche (2014)
FC	Field capacity of soil ($mm\ m^{-1}$)	89.8	Witney (1988)
F_N	Normal force (N)	31,392	$g = 9.81\ m\ s^{-2}$
m	Mass (kg)	3200	
S	Field speed, mean ($km\ h^{-1}$)	5	Witney (1988)
S_{Road}	Road speed, mean ($km\ h^{-1}$)	22.1–33.1	Varies with D_F (n)
s	Slippage (decimal)	0.2	ASAE (2000)
θ_{min}	Minimum allowed state of charge (decimal)	0.2	
θ_{max}	Maximum allowed state of charge (decimal)	1.0	
α	Gradient (%)	10	
η_{Field}	Field efficiency (decimal)	0.8	Witney (1988)
η_{Motor}	Motor efficiency (decimal)	0.95 (BED)	(Andersson, 2019) (Wasilewski et al., 2017)
		0.3 (ICE)	
$\eta_{Transmission}$	Transmission efficiency (decimal)	0.85	(Ryu, Kim, & Kim, 2003; Serrano, José, da Silva, Pinheiro, & Carvalho, 2007)
$\eta_{Battery}$	Battery efficiency (decimal)	0.97	
$\eta_{Charger}$	Charger efficiency (decimal)	0.95	Lucas, Trentadue, Scholz, and Otura (2018)
ρ_{air}	Density of air ($kg\ m^{-3}$)	1.225	Reif and Dietsche (2014)

Table A.2 – Constants and implement parameters used for calculating draft implement force (F_D) and power (P_D), ordered by task (ASAE, 2000)

Task (x)	f_i	A	B	C	D_T [m]	W^a [m]	F_D [kN]	P_D	C_0 [ha h^{-1}]	Range +/− %
Cultivation (Field cultivator)	1	46	2.8	0	0.10	2.6	9.98	33.6	1.0	30
Harrow (Spring-tine harrow)	1	2000	0	0	0.01	5	9.18	13.9	2.0	30
Roller packer	1	600	0	0	0.01	12.3	14.58	10.3	4.9	50
Sowing (Grain drill)	1	300	0	0	0.01	3.0	19.50	6.3	1.2	25
Ploughing (Mouldboard plough)	1	652	0	5.1	0.20	1.55	17.60	33.6	0.6	40
	P/W [kW m^{-1}]	P_D	W [m]	C_0 [ha h^{-1}]						
Fertiliser spreading	3.12	17.2	24	9.6						
Pesticide spraying	2.29	17.2	24	9.6						

[a]Maximum implement width based on the largest available implements for the chosen vehicle power, from the manufacturer Kvarneland and retailer Lantmännen Maskin at time of publication.

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Research Paper

Cost analysis of autonomous battery electric field tractors in agriculture

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Interest in the electrification of agricultural vehicles is increasing along with growing interest in autonomous vehicles. Individual technologies have been well-explored, but not their combined use and the effects on agricultural fieldwork. In this study, cost analysis was conducted based on a simulated vehicle system with 50 kW self-driving battery-electric drive (BED) tractors. The analysis included battery degradation due to cycling and the cost of inadequate machine capacity, as these factors are suspected to be problems for electric tractors. A dynamic discrete-event vehicle system model, a linear timeliness model and a one-dimensional battery cell ageing model were assumed. Costs obtained were compared with those of contemporary manned diesel-based systems. BED systems had equal or lower annual costs compared to conventional manned diesel-based systems; this was due to lower costs for fuel and maintenance, while providing adequate capacity and lower energy usage. Sensitivity analysis showed that operating costs were of greater significance than investment costs. The generally more expensive investment costs of BED systems were outweighed by the reduced operating costs for several different BED system systems. Battery degradation costs and timeliness were influential, but not sufficient to make the system uncompetitive. The synergistic effect of vehicular autonomy and BED outweighed several of the drawbacks of BED systems, such as frequent recharging, increased transport and reduced consecutive work time.

1. Introduction

Making agricultural systems autonomous can be an important component in increasing agricultural productivity, feeding the world and achieving sustainable food production (Bakken, Moore, & From, 2019; Lampridi et al., 2019). Vehicle electrification is seen as one of the main methods for reducing vehicular emissions and reliance on fossil fuels, both on and off road. Sweden aims to have its vehicle fleet independent of fossil fuel by 2030 and to have net zero CO_2 emissions by 2050,

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Nomenclature

A	Total arable area (ha)
a,b,c	Battery model parameters
A_n	Area of field *n* (ha)
BED	Battery electric drive
BES	Battery exchange system
BEV	Battery electric vehicle
$c_{B,cyc}$	Battery cost per eq. cycle (€)
CC	Conductive charging
CC/CV	Constant current/constant voltage
C_{AN}, C_{OW}, C_{OP}	Total annual cost, ownership cost and yearly operating cost (€ y^{-1})
C_x	Total investment/operating cost for component x (€)
c_x	Investment/operating cost for each unit of x (var.)
d	Inflation (%)
E_B	Battery energy content (kWh)
EOL	End-of-life (primary, for batteries)
E_{tot}	Total yearly energy requirement (kWh y^{-1})
EV	Electric vehicle
h	Vehicle work hours per day (h d^{-1})
i	Interest rate (%)
i_r	Real interest rate (%)
l_g	timeliness factor for grain *g* (kg ha^{-1} d^{-1})
MCTR	Mean cycles to replacement
MTTR	Mean time to replacement (yr)
n	Field number
N_B	Number of (additional) batteries
N_C	Number of chargers
N_{CA}	Number of additional chargers
N_{cycl}	Number of battery cycles
N_V	Number of vehicles
O_F,O_R,O_C	Fraction of time operator is required for fieldwork, road transport and charging (fraction)
P_C	Charger power (kW)
P_g	Grain price for the grain *g* (€ kg^{-1})
P_V	Vehicle power (kW)
R_x	Salvage value of component x (€)
S_n	Timeliness cost for field *n* (€ yr^{-1})
SoC	State-of-charge
T_D	Total active time (d)
t_n	Delay from optimal day for field *n* (d)
T_x	Economic lifetime for component x (y)
x_c	Relation between battery energy capacity and charger power (h)
Y	Yield (kg ha^{-1})
θ	State-of-charge (fraction)
θ_{EOL}	State-of-charge value at end-of-life (fraction)

with electrification listed as one of the vital tools in achieving this (The Government of Sweden, 2013).

In a previous study (Lagnelöv, Larsson, Nilsson, Larsolle, & Hansson, 2020), the technical possibility of a vehicle system utilising smaller, self-driving, battery-electric drive (BED) field tractors was explored. In terms of time required for spring and yearly operations they were found to be comparable with manned diesel vehicles and they were also better in terms of energy use. However, to achieve broad appeal and market uptake, a good understanding of the cost of the system is vital. Lagnelöv et al. (2020) provided a system model and technical system understanding but in this study the focus is on the cost of autonomous vehicles and battery electric systems. Previous research has examined the cost and utilisation of general autonomous systems (Lampridi et al., 2019; Marinoudi, Sørensen, Pearson, & Bochtis, 2019), performed cost analysis on autonomous row-crop cultivation (Goense, 2005) and analysed autonomous systems in specialist crops (Le, Ponnambalam, Gjevestad, & From, 2020; Reiser, Sehsah, Bumann, Morhard, & Griepentrog, 2019; Young, Kayacan, & Peschel, 2018). However, the cost of electric autonomous field tractor systems has not been thoroughly researched.

The possible cost to yield or quality loss due to lack of capacity in the system (i.e. lack of timeliness) and the cost and limitations of batteries have been identified as potential drawbacks for agricultural BED tractors (Caban, Vrabel, Sarkan, Zarajczyk, & Marczuk, 2018; Magalhães et al., 2017; Mocera & Soma, 2020; Moreda, Muñoz-García, & Barreiro, 2016). In cost analysis it is therefore important to include these drawbacks and their system effects.

Untimely or non-optimal operations can lead to indirect costs, due to yield losses or a decrease in crop quality. Prediction of optimal work time and the negative effects of non-optimal work time have been well studied (ASAE, 2000; Edwards, Dybro, Munkholm, & Sörensen, 2016; Gunnarsson, Spörndly, Rosenqvist, De Toro, & Hansson, 2009; Nilsson, 1976; Rotz & Harrigan, 2005; Savin, Matic-Kekic, Dedovic, Simikic, & Tomic, 2014; Witney, 1988). Witney (1988) identified untimely establishment, spraying and harvesting as the most important operations and concluded that adequate machine capacity is vital, but it is difficult to assess, partly due to the unique nature of each site and the erratic behaviour of the weather. The common approach is therefore to have overcapacity in the machine pool.

The effect of agricultural use and load cycles on electric vehicle (EV) batteries is not well analysed. The concern with the use of BED tractors in the field is that this heavy use will rapidly age the batteries and therefore make the system economically uncompetitive.

The aim of this study was to evaluate an autonomous battery electric vehicle (BEV) system for a Swedish agricultural context with regards to cost. Changes in timeliness and loss of battery capacity, and related costs, were studied specifically and included in the overall cost. The model developed in Lagnelöv et al. (2020) was used to develop basic data for the calculations, but in addition, a sensitivity analysis was made for several relevant variables, including component cost, charger power, degree of autonomy, and battery size, lifetime and cost.

2. Method

This section firstly presents the models used for battery ageing and timeliness, and then describes the economic calculations. Overall costs were calculated as a combination of annual ownership costs and operating costs, including battery and timeliness costs. The costs of ownership and operation were calculated from the inputs (number and size of vehicles, chargers etc.) or the main results from the system model (numbers of hours a driver is needed etc.). For timeliness and battery ageing, separate models were required, as shown in Fig. 1.

The discrete-event model from Lagnelöv et al. (2020) was used to simulate the analysed vehicle systems. The model simulates the machinery operations on a Swedish grain farm in the Uppsala region. To bring the farm machinery operations more in line with that commonly used in Sweden, a sow bed harrow replaced the spring tooth harrow used in Lagnelöv et al. (2020) with power use described by Lindgren, Pettersson, Hansson, and Norén (2002). The average power usage and working width are shown in Fig. 2. Additionally breakdown rates taken from ASAE (2000) were included in the simulations. The breakdown rates were the combined factors for a vehicle system with a field area of 200 ha and each breakdown was assumed to put the vehicle out of operation, leading to 12 h of downtime. The cost of repairing is included in the maintenance cost, so the only cost effect of a breakdown was a delay of operations. Due to being a less well-developed system it was assumed that the breakdown rate for the autonomous electric tractors was double that of the manned diesel tractors.

For timeliness, the model by Gunnarsson (2008) was used, which takes the delay in key operations for each field and turns it into an annual cost. For battery ageing, a one-dimensional battery cell model for NCA Li-ion batteries that connected voltage and capacity loss to the number of full use cycles was used. These results were then used in the main model to incorporate the effects of continuous degradation of the vehicle batteries. In addition, the results were used to dynamically determine the useful lifetime of the batteries before they needed replacing, which led to a cost per year or per cycle. All the costs were then summed to a total annual cost of operations.

2.1. *Battery ageing*

Battery ageing is a common electrochemical process that is dependent on different factors, including use pattern, depth of discharge, battery temperature, charge/discharge rate etc. (Barré et al., 2013; Uddin, Perera, Widanage, & Somerville, 2016). This often leads to EV batteries having a shorter life-spans than the vehicles they power, and this might require a change of battery before a change of vehicle. Therefore, it is important to estimate and include the effect of battery ageing in economic analysis of BEVs. For novel vehicle systems, the effect of battery ageing is important information when designing the system, especially if the work includes high-

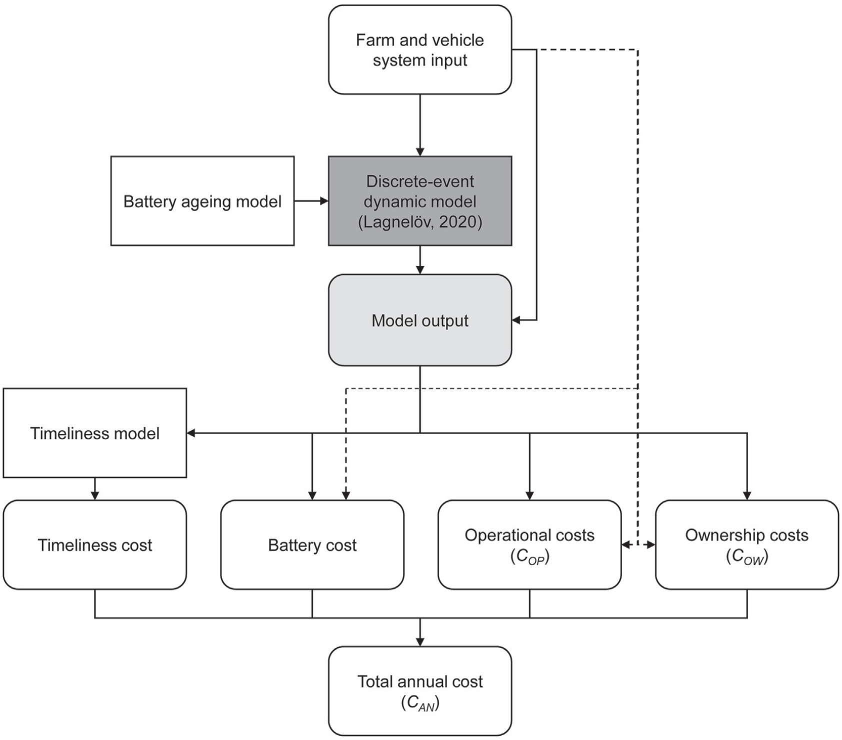

Fig. 1 – Overview of the models used (sharp-cornered boxes) and costs analysed (rounded boxes). The dotted lines indicate where system inputs were used for cost calculations.

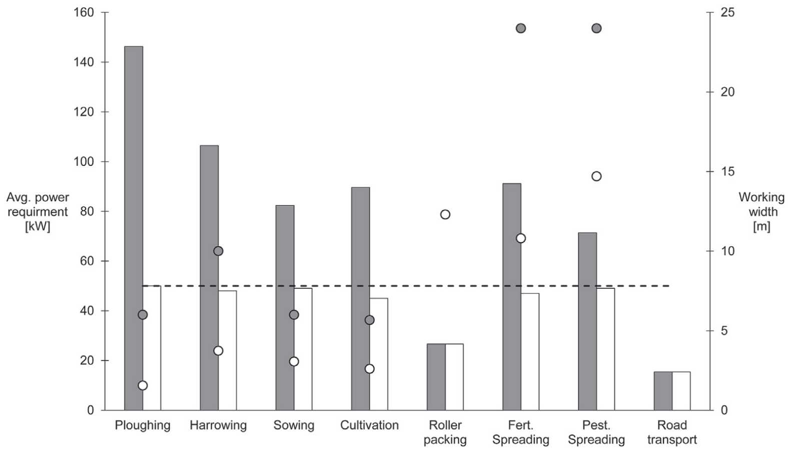

Fig. 2 – Average total power requirement (bars, left axis) and working width (circle markers, right axis) for the operations used in the simulations for the tractor sizes 250 kW (dark gray) and 50 kW (white). The maximum power of the 50 kW tractor is marked (dashed line).

power use of the battery over a longer period, as is the case in agricultural fieldwork. In this regard, the use of batteries in heavy off-road applications is different from their use in on-road personal vehicles. In this study, battery ageing was characterised as capacity of NCA batteries depending on the number of cycles for each battery and the charge rate (C-rate) of the charging station.

2.1.1. *Battery model*

A one-dimensional battery cell model was created using the ‘Lithium-Ion Battery’ module in COMSOL Multiphysics 5.5 (COMSOL AB, Stockholm, Sweden). In this model, graphite is used as the negative electrode (thickness 55 μm), $LiPF_6$ in 3:7 EC:EMC as electrolyte (30 μm) and NCA ($LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$) as the positive electrode (40 μm). The model was based on the porous electrode theory and concentration solution theory (Thomas, Newman, & Darling, 2002). It included ageing in the graphite electrode, where a parasitic solid electrolyte interface (SEI)-forming reaction results in irreversible loss of cyclable lithium. The kinetic expression for the SEI-forming reaction used here was based on work by Ekström and Lindberg (2015). More details regarding this model can be found in the COMSOL library (COMSOL Multiphysics, 2020). Specific simulation inputs can be found in Table A1.

2.1.2. *Model assumptions and adaptation*

Calendar ageing of the batteries was omitted, as it is less impactful for battery degradation than the number of cycles and as one of the defining characteristics of Li-ion batteries is their low capacity fade during storage (Barré et al., 2013). Ambient temperature was assumed to remain constant at 293 K and the vehicle was assumed to have a temperature control system with adequate ability to keep a constant battery temperature of 293 K during charging and discharging. The state-of-charge (SoC) is limited in the system model to stay above 20% at all times, giving a maximum depth-of-discharge interval of 20–100%, with fast charging applicable in the interval 20–80% and slower charging during the interval 80–100%. Considering field operations and type of use, it was assumed that C-rate and number of battery cycles (N_{cycl}) would be the most influential direct factors (Uddin et al., 2016; Wenzl et al., 2005).

In the model, the cycles are calculated for each battery and all batteries in operation are assumed to be used equally. The number of cycles for each battery is carried over between each year according to:

$$N_{cycl}(i) = N_{cycl}(i-1) + \frac{N_{cycl}(i)}{(N_B + N_V)} \tag{1}$$

where N_{cycl} is the number of cycles at the end of year i, N_V is the number of vehicles (as each vehicle carries one battery) and N_B is the number of spare batteries in the system.

Vehicles continue their operations even if the SoC of the batteries dips below 80%, with the batteries being replaced between working seasons. The SoC of a battery is related to the number of cycles as:

$$\theta = aN_{cycl}^3 + bN_{cycl}^2 + cN_{cycl} + d \tag{2}$$

where a, b, c and d are curve fitting parameters of the third-order polynomial curve used as a representation of the simulated values. High-order polynomials have been used to represent battery capacity fade and voltage curves by e.g. Stamps, Holland, White, and Gatzke (2005).

When the capacity fade is at $\theta = 0.8$, the battery is scheduled for replacement in the model, as this is common practice in the industry (Berg, 2015). The number of cycles this takes is denoted mean cycles to replacement (MCTR). The MCTR for each individual battery is the same, irrespective of E_B and N_B, but the mean time to replacement (MTTR) in years will change depending on the number and size of the batteries. Since the cycles were disturbed roughly evenly between the different batteries in the system, it was assumed in this study that MTTR increases with a higher number of batteries in the system and with larger batteries.

2.2. Timeliness

When studying timeliness, there is often mention of an optimum day, i.e. the day where the specific operation will produce the highest yield (Gunnarsson, 2008; Witney, 1988). In this study, the timeliness of sowing was the main focus, as the simulation model used (Lagnelöv et al., 2020) concentrates on operations performed by tractors. Of those, sowing was viewed as having the greatest impact and other operations were considered generally as being preparation for sowing.

It was assumed that the first workable day of the year was optimal for spring-based sowing and that the first day after harvesting finished in autumn was optimal for autumn sowing. This was based on the concept of delayed scheduling presented by Gunnarsson (2008), where all the time that elapses beyond the optimal day is assumed to incur a yield loss. Since harvesting was not included in the simulation, it was assumed that harvesting was carried out with adequate capacity and that no timeliness penalty was incurred.

The slope and shape of the curve displaying yield loss are different in different sources, e.g. Gunnarsson (2008) and ASAE (2000) characterised the yield loss as linear and Witney (1988) characterised it as parabolic. Here the linear method was used, with the timeliness factors taken from Gunnarsson (2008).

For each scenario, the total time elapsed from the first possible day was measured. The cost of yield loss for a specific field n (S_n, in € y^{-1}) due to non-optimal sowing date was assumed to depend linearly on the delayed scheduling described by Gunnarsson and Hansson (2004) and Gunnarsson et al. (2009).

A dynamic simulation was used to simulate many of the events described by Gunnarsson and Hansson (2004) and combine them into a single parameter for the particular field, n (see Table 1). This allowed use of the following equation, as also proposed by Nilsson (1976) and used by Gunnarsson and Hansson (2004):

$$S_n = l_g \times t_n \times p_g \times A_n \tag{3}$$

where l_g is the timeliness factor in kg ha^{-1} d^{-1} for grain g, t_n is the time delay from the optimal day in d for field n, p_g is the grain price in € kg^{-1} for grain g and A_n is the total crop area in ha for field n. The delay, t_n, was measured at the completion of each field.

The optimal day was calculated for sowing and was set as the first workable day of the year. As explained in Lagnelöv et al. (2020), in the model it is assumed that the simulation period starts with the soil saturated, due to thawing and precipitation, so it takes a period of time before the first workable day for the soil, and it is from that day that the delay is calculated.

To calculate the cost of the delay, the optimum price for grain, p_g, and the yield needed to be defined. The price of grain was taken from the agricultural wholesale dealer Lantmännen's prices for 2019, and yield was based on the normal yields given in Statistics Sweden (2019) for the Uppsala region for 2018 (Table 2). The timeliness factors proposed in Gunnarsson (2008) were used (Table 2). For some grain crops, only the factor values for organic production were available, but this was assumed to have little effect on the results.

2.3. Economic analysis

2.3.1. Cost calculation

The cost of the autonomous BED system was calculated using the total annual cost of operation (C_{AN}) and compared with the calculated cost for a diesel counterpart, and with literature values. The calculation method based on combined investment, ownership and operating costs of vehicles found in Wu, Inderbitzin, and Bening (2015) and Lampridi et al. (2019) was adapted and used, including straight-line depreciation as seen in Eq. (4). When considering the cost of an autonomous system and agricultural robotics, the methods found in Lampridi et al. (2019) and Marinoudi et al. (2019) were used.

$$C_{AN} = C_{OW} + C_{OP} \tag{4}$$

where C_{AN} is the annual cost of operations, C_{OW} is the ownership cost calculated as shown in Eq. (5) and C_{OP} is the operating cost, calculated as shown in Eq. (6). All values are in € yr^{-1}.

C_{OW} is the combined cost of investment (fixed depreciation cost and capital cost) as an equivalent annual cost with the average interest rate method used, as used by Lampridi et al. (2019):

$$C_{OW} = \sum \frac{C_x - R_x}{T_x} + \frac{(C_x - R_x)}{2} i_r \, ; [x = B,\ C,\ CA,\ BCS,\ A,\ V] \tag{5}$$

$$C_{OP} = \sum C_y ; \left[y = \begin{cases} E,\ ME,\ O\ (BED) \\ D,\ MD,\ O\ (Diesel) \end{cases} \right] \tag{6}$$

where c_x is the component investment cost in €, R_x is the salvage value in € (normally 10% of purchase price), T_x is the economic lifetime in years and C_y is the operating cost in € yr^{-1} (where x and y are the specific component subscript for the investment and operating costs respectively, described in Tables 3 and 4) and i_r is the real interest rate correction factor (Lampridi et al., 2019), calculated as shown in Eq. (7).

$$i_r = \frac{i + d}{1 + d} \tag{7}$$

where i is the interest rate and d is inflation, both in %.

Here, d was set to 2% to match Sweden's inflation goal, and i was set to 2.75%, which is a reasonable interest rate for agricultural businesses (L. Hylander (Swedbank), personal communication, June 17, 2020).

The component costs and equations for each parameter are shown in Tables 3 and 4. Sections 2.3.2, 2.3.3, 2.3.4, 2.3.5, 2.3.6, 2.3.7, 2.3.8 and 2.3.9 explain the costs, sources and assumptions for each category. When no data were available, it was assumed that both the BED system and the corresponding diesel tractor system had equal costs. This included vehicle housing, seeds, fertilisers, pesticides, insurance and non-field-related farming expenses. For all conversions between currencies, the following rates from May 7, 2020 were used: 1 € = 10.64 SEK = 1.10 US$.

Table 1 – Field number and area in the simulations, and type of grain grown; O = oats, W.W = winter wheat, S.W = spring wheat and B = barley.

Field no. (n)	1	2	3	4	5	6	7	8	9	10	11	12
Area (A_n) [ha]	10	16	22	13	15	26	6	14	22	28	15	13
Grain	O	W.W	B	B	S.W	O	W.W	O	S.W	W.W	B	S.W

Table 2 – Timeliness factors and yields for the grain crops assumed in simulations. Timeliness factors from (Gunnarsson, 2008) and yield data from Statistics Sweden (2019).

	Winter wheat	Spring wheat	Barley	Oats
p_g, Grain price [€ kg^{-1}]	0.130	0.130	0.118	0.143
Y_g, Yield [kg ha^{-1}]	5658	4221	4581	3823
l_g, Timeliness factor [kg ha^{-1} d^{-1}]	55	59[a]	40	23[a]
Timeliness, [% d^{-1}]	1.1	1.5	1.0	0.9

[a] Value for organic production instead of conventional.

2.3.2. *Charging infrastructure*

The cost of chargers included the price for the charging station, the grid connection cost, casing, site establishment, wiring, installation safety control and the cost of contract work. The total cost for this ranged from 35,000–80,000 €, according to Swedish Energy Agency (2019). The assumed cost was set to $c_C = 50{,}000$ €. It was assumed that the full cost of establishing charging infrastructure was required for the first charging station ($N_C = 1$), and that any additional charging ($N_C > 1$) just required investing in additional charging stations, which was priced at $c_{CA} = 25{,}660$ € for a Siemens mode 3 fast charger (Engström & Lagnelöv, 2018). It was assumed that the connection of charging stations were within the limit of the farms pre-existing power capacity and that no upgrade in fuse size was needed.

2.3.3. *Battery changing system*

An industry sector that has similar needs to the agricultural sector, and has solutions for battery replacement technology, is the forklift sector. Its solutions are less complex and costly than the large-scale systems found in mining vehicles or buses. For example, a battery storage and replacement system used for forklift trucks from the Solus Group costs 5000–10,000 €, depending on capacity and complexity (Solus Group, 2019). The higher cost ($c_{BCS} = 10{,}000$ €) was chosen here, since knowledge of the system is low.

2.3.4. *Tractor prices*

The cost of investing in a new field tractor was calculated using Eq. (8) which was developed by Engström and Lagnelöv (2018) and estimates the vehicle price based on the rated engine power. The equation is regression-based and uses data from Swedish tractor retailers. The equation was verified using official data on the average price of tractors in 2018 (Statistics Sweden, 2019), with acquisition values from Maskinkalkylgruppen (2020), and compared with linear relationships between price and rated power presented in Goense (2005). It was assumed that engine/motor and other driveline components were included in this price. To represent the lack of mass production for BED systems, it was

Table 3 – Costs, lifetime and equations used to calculate combined cost of investment (C_{OW}), where C (capital) is the total investment cost in € and c (lower-case) is the investment cost per component or unit in €. Sources given in sections 2.3.2, 2.3.3, 2.3.4, 2.3.5, 2.3.6, and 2.3.7.

Component (subscript)	Component cost (c_x)	Assumed economic lifetime (T_x) [yr]	Equation
Battery (B)	146 € kWh^{-1}	(see section 2.3.6)	$C_B = c_B\, E_R (N_V + N_B)$
Charger (C)	50,000 €	20	$C_C = c_C + (N_C - 1) c_{CA}$
Additional charging stations (CA)	25,662 €	20	
Battery changing system (BCS)	10,000 €	20	$C_{BCS} = c_{BCS}\, N_{BCS}$
Autonomy system (A)	17,446 €	15	$C_A = c_A\, N_V$
Tractor, $P_R = 50$ kW (V)	45,005 €	15	$C_V = \dfrac{N_V\,(8107.2 \times P_R + 10970)}{10.64}$
Tractor, $P_R = 250$ kW (V)	191,550 €	15	

Table 4 – Costs and equations used to calculate operating costs of the system (C_{OP}). Sources given in sections 2.3.2, 2.3.3, 2.3.4, 2.3.5, 2.3.6, 2.3.7, 2.3.8 and 2.3.9.

Parameter	Variable	Component cost (c_x)	Units	Yearly cost [€ yrs^{-1}]
Electricity	C_E	0.08	€ kWh^{-1}	$C_E = c_E\, E_{tot}$
Diesel	C_D	0.086	€ kWh^{-1}	$C_D = c_D\, E_{tot}$
Maintenance Diesel	C_{MD}	48.8	€ ha^{-1}	$C_{MD} = c_{MD}\, A$
Maintenance BED	C_{ME}	35.1	€ ha^{-1}	$C_{ME} = c_{ME}\, A$
Operator	C_O	28.2	€ h^{-1}	$C_O = \sum c_O\, a\, h_d$
Battery cost per cycle	$C_{B,cyc}$	(see section 2.3.6)	€ cycle^{-1}	$C_{B,cyc} = c_{B,cyc} N_y$

assumed that the BED tractors had a 15% increase in investment cost compared to Eq. (8).

$$c_T\,[€] = (8107.2 * P_R + 10970)[SEK] * \frac{1}{10.64}\,[€/SEK] \tag{8}$$

2.3.5. *Autonomous systems*

The system architecture and sensory requirements for autonomous systems can vary between different sectors, vehicles and levels of autonomy. There is a lack of data for autonomous systems in the agricultural sector, which necessitates use of data from other sectors. Engström and Lagnelöv (2018) used a 10,000 € template value based on the increased price of Volvo cars when equipped with autonomous capacity, which is similar to the findings of Daziano, Sarrias, and Leard (2017) for the add-on Cruise-RP1 system (Cruise, San Francisco, CA, USA), priced at 10,000 $ (~9000 €). Vedder, Vinter, and Jonsson (2018) estimated that building a vehicle with self-driving capacity was possible at prices from 2000 €. Higher estimates have been given, putting the price for full autonomous capability in cars at 70,000 $ (Fagnant, Kockelman, & Bansal, 2015). Bösch, Becker, Becker, and Axhausen (2018) assumed that for fleet-based cars, the price increase would be 20% higher for cars with autonomous systems compared with those without, a value that Brundrett (2014) found applicable for autonomous mining vehicles. The autonomous diesel-powered tractor Robotti (Agrointelli, Aarhus, Midtjylland, Denmark) is priced in range as modern manned tractors, 133,170–192.447 € depending on rated power and options (F. Rom (Agrointelli), personal communication, January 20, 2021). It was assumed that the cost for the total autonomous system of SAE level 4 or above (SAE, 2018) was 20% of the average Swedish tractor price (Statistics Sweden, 2019), which resulted in $c_A = 17{,}450$ €.

2.3.6. *Batteries*

In a summary by Comello and Reichelstein (2019), the market price for a Li-ion battery system in the US was projected to range between 113 and 172 € kWh^{-1} in 2020. Tsiropoulos, Tarvydas, and Lebedeva (2018) estimated a cost in the range of 170–215 € kWh^{-1} for Li-ion battery packs in the EU in 2017. This was based on predictions by Nykvist and Nilsson (2015) of a possible pack cost of 182 € kWh^{-1} in 2020. The actual cost will depend on cell chemistry, producer and production method (Tsiropoulos et al., 2018). Here, the cost, c_B, was set to 146 € kWh^{-1}, as it fitted multiple predictions, was the average price given by Comello and Reichelstein (2019) and was close to the 2019 market average of 142 € kWh^{-1} (McKerracher et al., 2020). For clarity, batteries are shown as both an investment cost and as an operating cost. Therefore it may be easier to calculate the cost per year, cycle or unit of energy stored, which is shown in Appendix B.

2.3.7. *Fuel*

Both electricity and diesel were considered as fuels in this study. The base price of diesel was taken from the Swedish average price for March 2020, as reported by SPBI (2020), and reworked to the current net price for the agricultural sector. Swedish agricultural businesses are exempt from VAT (25%) on diesel and are entitled to a carbon tax refund of 181.8 € m^{-3} diesel. The total pump-price of 1.32 € l^{-1} is thereby reduced to 0.87 € l^{-1}. Further conversion to price per unit of energy was made using the density (845 kg m^{-3}) and net calorific value (43.1 MJ kg^{-1}) of diesel found in Reif and Dietsche (2014) for a total price of 0.086 € kWh^{-1}. The price for electricity, 0.08 € kWh^{-1}, was taken from the official Swedish statistics for businesses with annual consumption between 20 and 500 MWh (Statistics Sweden, 2020).

2.3.8. *Maintenance*

The maintenance costs for agricultural tractors were taken from Pettersson and Davidsson (2009, pp. 1401–4963), who analysed the maintenance costs for Swedish field tractors in grain production on farms with 150–300 ha. This was verified with data from Olt, Traat, and Kuut (2010) for similar machines and production types. This put the maintenance costs within the range 20.5–48.8 € ha^{-1} for diesel systems, and the highest value of 48.8 € ha^{-1} was chosen for the present analysis.

For BED tractors there are less available data. Sources studying on-road vehicles give the maintenance cost reduction for BED tractors compared with diesel at 19–28% (Delucchi & Lipman, 2010; Propfe, Redelbach, Santini, & Friedrich, 2012), which puts the maintenance costs for BED tractors in the range 18.8–39.5 € ha^{-1}. A maintenance cost of 72% of that of a diesel tractor (35.1 € ha^{-1}) was chosen.

2.3.9. *Driver & operators*

For manned vehicles, it was assumed a driver needed to be hired. It was assumed that this driver was contracted on a per-hour basis related to the active time of the tractor, which is the sum of the time spent performing fieldwork, road transport and refuelling. For the autonomous systems, it was assumed that an operator was required to control the vehicle during more challenging operations and for general management of the system. The fraction of vehicle time assumed to need an operator was called operator factor, O. It was defined as a fraction between 0 and 1, and describes the fraction of hours that the vehicle needs to be managed by an operator for that specific task, with 0 being fully autonomous and 1 being fully monitored. Engström and Lagnelöv (2018) used a value of 0.1 for all tasks and Goense (2005) used 0.2 for field operations based on the complexity level of different field manoeuvres, but did not include road transport or refuelling. In this study, different values were set for fieldwork ($O_F = 0.2$, i.e. 20% of all fieldwork hours needed to be monitored), road transport ($O_R = 0.3$) and refuelling ($O_C = 0.1$), as they had different levels of complexity, with road transport assumed to be the most complex task.

The operator was assumed to have an hourly cost of 28.2 €, which is the rate recommended for the total cost of an experienced employee in the agricultural sector, including social benefits, taxes, vacation and 15% write-up for non-productive time (Maskinkalkylgruppen, 2020). For the manned systems, the values were verified with the normal yearly tractor use of 650 h y^{-1} from Maskinkalkylgruppen (2020), and were found to be within 10% of that value.

2.4. *Simulation inputs*

The vehicle system cases with the parameters shown in Table 5 were simulated and analysed, unless specifically

Table 5 – Base case simulation inputs for the battery electric drive (BED) tractor and inputs for the reference cases with one and two diesel tractors (D1, D2).

Case name	BED	D1	D2
Number of vehicles (N_V)	2	1	2
Vehicle power (P_V, kW)	50	250	250
Battery energy eq. carried (E_B, kWh)	50	1315	1315
Number of extra batteries (N_B)	2	–	–
Charging power (P_C, kW)	50	30,345[a]	30,345[a]
Number of chargers/fuel pumps (N_C)	1	1	1
Number of battery exchange stations (N_{BCS})	1	–	–
Daily working time (h, h d^{-1})	24	10	10

[a] Diesel pump with a flow of 50 L min^{-1}.

stated otherwise. They were chosen as a previous study found that BES performed slightly better and that a two-vehicle system provided adequate overall capacity for 200 ha, which was explored in Lagnelöv et al. (2020). The case D1 was chosen as being a reasonable diesel counterpart and D2 was chosen to represent a system with overcapacity.

The inputs were used in the dynamic discrete-event model of a 200 ha Swedish grain farm presented in Lagnelöv et al. (2020). The weather data for the years 2008–2018 were used in the soil water balance sub-system in the model, as the model was run for those years, so some results are 11-year averages.

3. Results

This section firstly presents the results of the simulation concerning battery ageing and timeliness, and then calculates the system cost from those results.

3.1. *Battery ageing*

Battery ageing due to cycling at different charging rates was simulated as described in section 2.1 and the results are shown in Fig. 3. The results for the capacity fade were fitted with third-order polynomials and were used in the model as an approximation of the capacity fade due to cycling. The polynomial constants were decided by the charging rate of the chargers, as depicted in Table 6.

The choice of charging rate for each case was determined using Eq. (9) and Eq. (10). The polynomial they represent was used as input in the main model:

$$C-rate = \begin{cases} 4C, & 2 \le x_C \\ 1C, & 0.5 \le x_C < 2, \\ 0.1C, & x_C < 0.5 \end{cases} \tag{9}$$

$$x_C = \frac{E_B}{P_C} \tag{10}$$

where x_c is the relationship between battery energy (E_B) and charging power (P_C) in h, and is used as a metric to decide the C-rate.

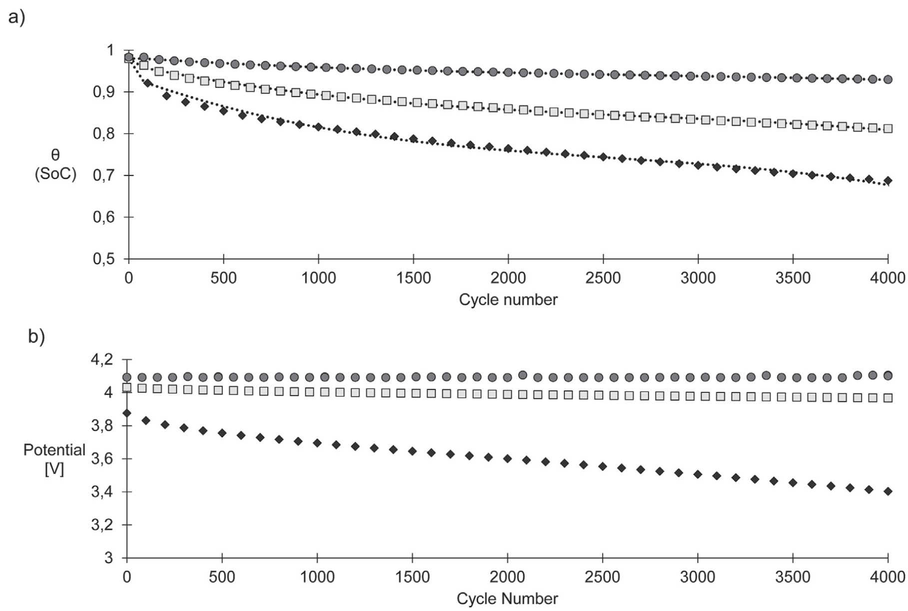

Fig. 3 – Decrease in (a) state-of-charge (SoC) and (b) voltage as a function of cycle number, simulated for three different charging rates: C/10 (circles), 1C (squares) and 4C (diamonds). Line-fitting curves from Eq. (2) (dotted lines) for the three different charging rates are shown in (a).

Table 6 – : Parameters used in Eq. (2) for different charge rates shown in Fig. 3.

C-rate	A	b	c	d	R^2
0.1C	$-8.81 * 10^{-13}$	$7.65 * 10^{-9}$	$-2.97 * 10^{-5}$	0.9820	0.997
C	$-3.37 * 10^{-12}$	$2.77 * 10^{-8}$	$-9.60 * 10^{-5}$	0.9655	0.994
4C	$-7.07 * 10^{-12}$	$5.43 * 10^{-8}$	$-1.69 * 10^{-4}$	0.9371	0.982

3.2. *Battery replacement*

A higher charging rate led to a shorter charging time and higher productivity, but it also aged the battery more rapidly than lower charging rates. This can be seen in Fig. 4, as MTTR for the given system at 4C was 2 years, while the same system had a MTTR of 7 years with 1C. For the C/10 charging rate, the chosen system did not reach the point of battery replacement in the 11 years simulated.

The limit for end-of-life (EOL) was set at 80% of starting capacity and the different charging rates reached it in differing amount of cycles: 4C reached it in 1200 cycles, 1C in 4240 cycles and C/10 in 7760 cycles.

3.3. *Timeliness*

A plot of the average delay for different vehicle systems (Fig. 5) revealed that the BED system has a longer delay in the spring than the systems with manned diesel tractors (D1 & D2). It is worth noting that the delay between fields was not insignificant, as even the best cases showed an average delay of 20 days for the highest numbered field. For autumn, none of the systems showed a long delay compared with the spring period.

The sowing interval for the BED system (Fig. 6) was within the range stated in Myrbeck (1998), with a comparable delay in the spring period to the 1-vehicle system of diesel tractors (D1) and with increased delay compared with the 2-vehicle system (D2). The autumn period sowing interval was short in all three scenarios and all systems were within the stated interval. However, since harvest was not simulated, but was simply assumed to be completed at the start of the autumn period, it is plausible that the starting date for sowing should be akin to that stated by Myrbeck (1998).

3.4. *Economics*

3.4.1. *Timeliness*

The delay for each grain and field in the three cases can be seen in Fig. 5. The cost for the delay for the BED case was 20,846 € in total, 18,370 € for the spring-sown crops and 2476 € for the winter wheat. The total yield loss was 30.1% compared with the optimum. For the diesel cases, the corresponding yield loss was 19.6% (D1) and 10.6% (D2), which resulted in costs of 13,569 € (D1) and 7321 € yr^{-1} (D2).

3.4.2. *Battery and energy cost*

The battery cost for the BED case, with 4 × 50 kWh NCA li-ion batteries, was 29,200 € in investment costs. The average yearly energy use was 91,462 kWh and the average number of equivalent cycles was 2464 cycles yr^{-1} (616 per battery and year). With a charging rate of 1C, the system had a theoretical MTTR of 6.8 years (7 years in simulation) and a MCTR of 4240 cycles. Using linear depreciation, this resulted in a cost of 6.8 € $cycle^{-1}$ or 0.17 € kWh^{-1}. The total energy cost (including electricity and battery cost) was then 0.97 € kWh^{-1}, compared with 0.86 € kWh^{-1} for diesel. Compared with the diesel cases, the BED system had lower energy consumption (54% of D1 and 52% of D2) and fuel costs (49–50% lower). The batteries made up 6% of the total operating costs and 14% of the investment costs for the BED case.

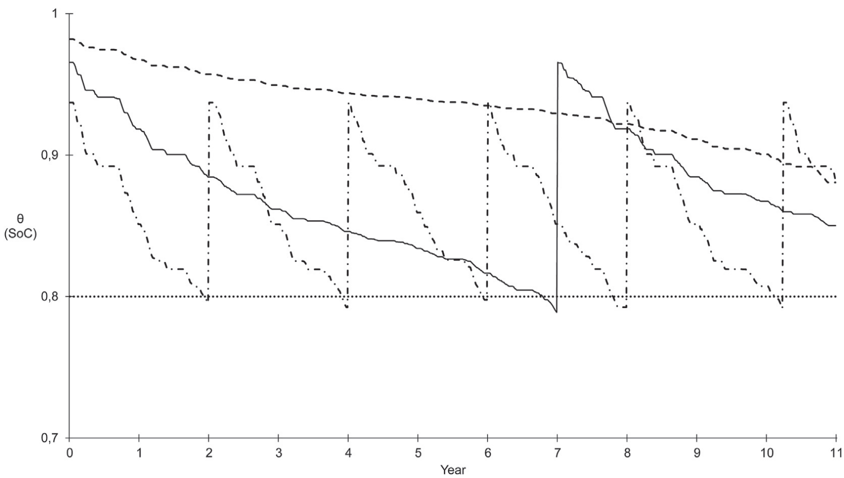

Fig. 4 – Capacity fade and replacement rate for three different charging rates, 4C (dash-dotted line), 1C (full line) and C/10 (dashed line) over 11 years. Simulation of a system of four batteries with energy content of 50 kWh, assuming even load on the batteries. End-of-life (θ_{EoL}) set at 0.8 (dotted line) and the battery packs were replaced at the end of the year where the system on average reached θ = 0.8. Calendar ageing not included.

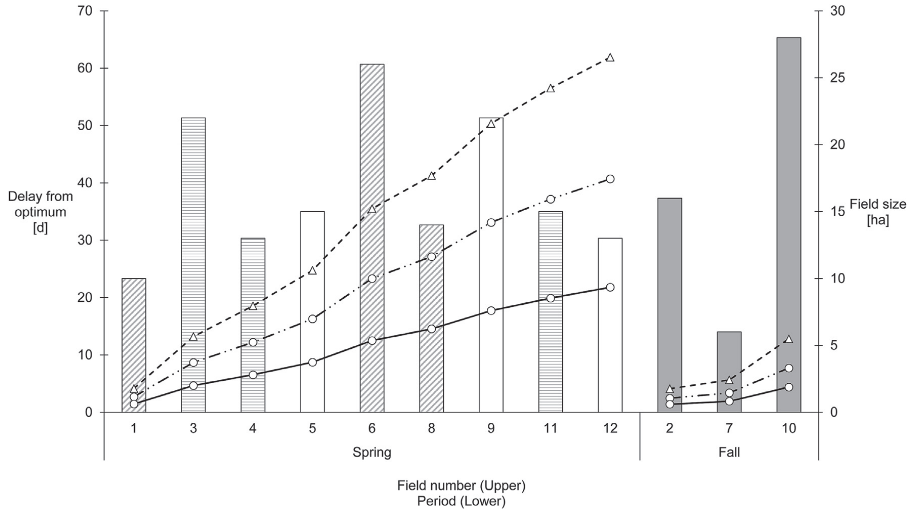

Fig. 5 – Average delay (lines, left axis) from the optimum date of sowing for scenarios with a battery electric drive (BED) tractor (dashed line) and a conventional manned diesel tractor system with two tractors (D2; full line) and one tractor (D1; dashed double-dotted line). Field sizes (bars, right axis) are shown, with the pattern and shade in columns denoting the type of grain crop grown in the field (winter wheat (grey), spring wheat (white), barley (vertical) and oats (diagonal)).

3.4.3. *Investment, operating and total annual costs*

The total cost of investment for the autonomous BED system with BES was 218,868 €, and the annual cost was 57,002 € yr^{-1}. The BED system had slightly higher investment costs and lower operating costs than the 1-vehicle diesel system (D1) and lower costs of both compared with the 2-vehicle system (D2) (Fig. 7). The investment costs for D1 were 196,554 € and the annual costs were 69,774€ yr^{-1}, while the investment

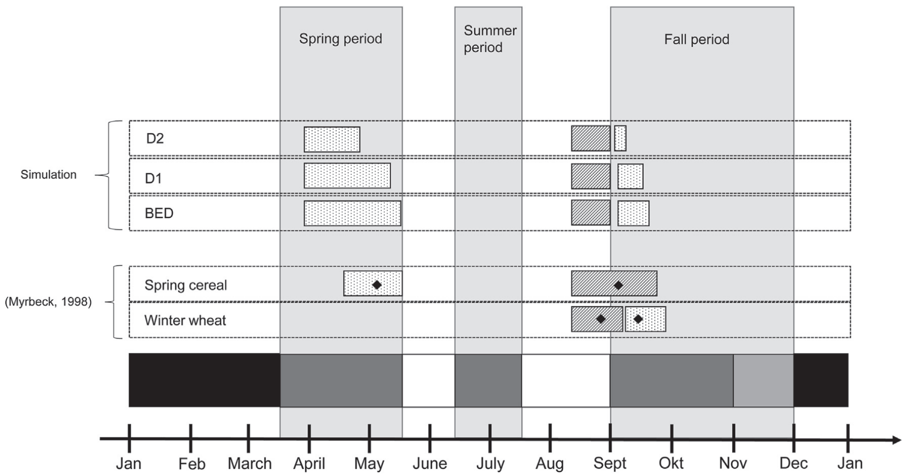

Fig. 6 – Actual sowing (dotted pattern) and harvesting (diagonal pattern) interval with mean values (black diamond) for central Sweden from Myrbeck (1998) and simulated sowing dates in scenarios with a battery electric drive (BED) tractor and a conventional manned diesel tractor system with one (D1) and two (D2) tractors. The three work periods are indicated in light grey, while non-active periods (black) and the growing period (white) are shown in the bottom bar. A one-month reserve period (medium grey) was included in the autumn period to make sure the simulation ran to completion. Ploughing was the only task performed during the reserve period.

costs for D2 were 393,108 € and the annual costs were 80,656 € yr^{-1}.

The largest fraction of the investment costs for the BED system was purchase of the tractor (41%) followed by installation of the charging system (23%) and the autonomous system (16%). For the diesel systems, the investment costs were similar for both D1 and D2, and comprised only purchase of tractor/s (97%) and cost of interest (3%).

For the diesel cases the three largest components of the annual cost (C_{AN}) were cost of investment (C_{OW}), operator cost and fuel, contributing 67–79% of the total operating costs (Fig. 8). For the BED case the three largest components were timeliness (30%), C_{OW} (23%) and operator cost (23%) for a total of 76% of $C_{AN.}$ Timeliness was a relevant component for the operating costs for all cases, at 20,847 € y^{-1} (30%) for the BED system, 13,569 € y^{-1} (19%) for D1 and 7321 € y^{-1} (9%) for D2.

3.5. *Sensitivity analysis*

A sensitivity analysis of several parameters was performed to assess their influence on different costs. The costs of batteries, autonomous system, charger installation, operator and electricity were varied in the BED case, to gain an understanding of their influence on the yearly cost of operations. In addition, the interest rate, timeliness factors, economic lifetime and the autonomous fraction of different operations and activities for the autonomous systems were varied. Absolute change, absolute sensitivity and relative sensitivity were measured.

3.5.1. *Parameter-based sensitivity analysis*

Table 7 shows the absolute sensitivity and the relative sensitivity for some key parameters included in the cost analysis. Relative sensitivity is denoted as the change in the total annual cost given a change of one unit in the given parameter.

3.5.2. *Rate of autonomy and operator factor*

The amount of autonomy is a key concept in the analysis of self-driving vehicle systems. Discussions on autonomous vehicles in agriculture usually focus on the amount of autonomy in fieldwork (Engström & Lagnelöv, 2018; Goense, 2005; Oksanen, 2015). However, for an independent generalist vehicle it is also necessary to consider additional activities, such as charging and road transport. The intricacies of on-road autonomy are a complex subject outside the scope of this article, but the scenarios of fully manned/monitored drive and fully autonomous operation were explored as a cost function, as shown in Table 8.

3.5.3. *Battery cost and lifetime*

As mentioned previously, the cost of the batteries was assumed to be low compared with other annual costs, but it is still critical for any electric vehicle. To verify the choices made and see the potential effect of other assumptions on prices and lifetimes, these parameters were varied independently.

As can be seen in Fig. 9b, the annual battery cost varied linearly with the pack cost. The battery cost was a small part of the total annual cost for all values tested and, even with the highest price in the interval, 330 € kWh^{-1} (Nykvist & Nilsson, 2015), the total annual cost was still lower than for D2 and similar to D1. The operational lifetime of the battery before replacement was important for the battery cost, as the cost decreased exponentially with increased lifetime (Fig. 9a). Extending the battery lifetime beyond the first few years is paramount to keep a low annual cost.

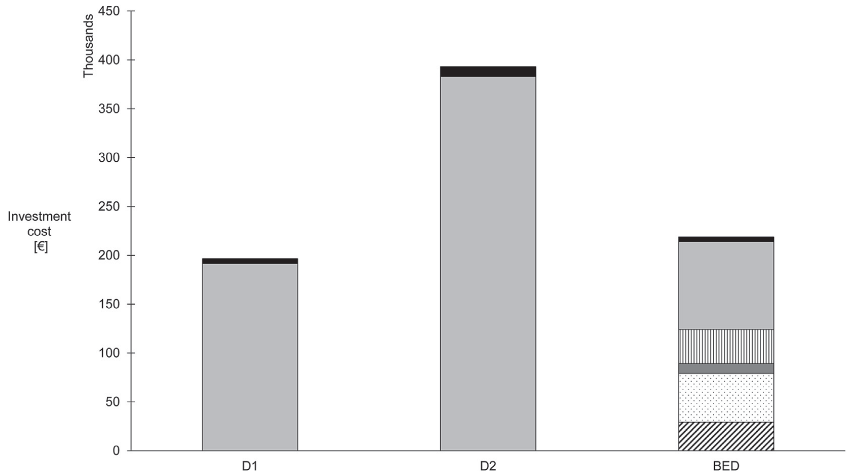

Fig. 7 – Investment costs (C_{OW}) in € for a simulated battery electric drive (BED) tractor system with autonomous capacity and two manned diesel counterparts (D1, D2). Columns show the cost of the tractor (grey), battery (diagonal stripes), charger system (dotted), battery changing system (dark grey), autonomous system (vertial stripes) and cost of interest (black).

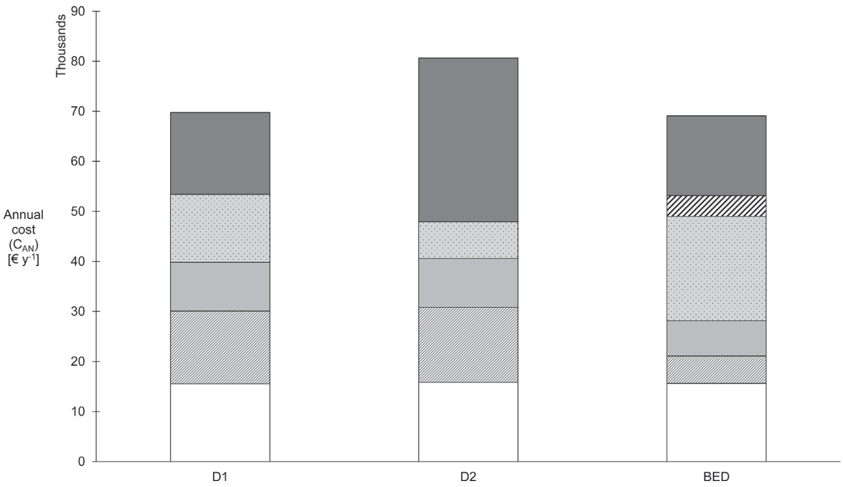

Fig. 8 – Annual cost of operation (C_{AN}) in € yr^{-1} for a simulated battery electric drive (BED) tractor system with autonomous capacity and two manned diesel counterparts (D1, D2). Columns show the annual costs of operator (white), fuel (thin diagonal stripes), maintenance (grey), timeliness (dotted on light grey background), batteries (broad diagonal stripes) and C_{OW} (annual cost of investment, dark grey).

Table 7 – Change in total annual cost given a change in a single parameter and relative sensitivity for different parameters influencing the annual cost in the battery electric drive (BED) tractor scenario. The closer the relative sensitivity is to one, the more sensitive the annual cost to changes in that parameter. Relative sensitivity of T_x is not shown as it is non-constant. In addition, changes deemed unrealistic are represented with a dash (–).

Parameter change	Absolute sensitivity, in %				Relative sensitivity
	−50%	−25%	+50%	+100%	
Investments					
Charger (c_C)	−3.3	−1.6	+3.3	+6.5	0.07
Battery (c_B)	–	−1.5	+2.9	+5.8	0.06
Tractor (c_V)	−5.6	−2.8	+5.6	+11.1	0.11
Autonomous system (c_A)	−2.2	−1.1	+2.2	+4.3	0.04
Operating costs	−50%	+50%	+100%	+200%	
Operator (c_O)	−11.3	+11.3	+22.6	+45.2	0.23
Electricity (c_E)	−4.0	+4.0	+7.9	+15.9	0.08
Timeliness factor (l)	−15.1	+15.1	+30.2	+60.3	0.30
Other	−50%	+50%	+100%	+200%	
Interest rate (i_r)	−1.9	+1.9	+3.8	+7.6	0.04
Economic life (T_x)	+16.4	−5.5	−8.2	–	–

Table 8 – Change in annual cost (C_{AN}, in %) compared with the battery electric drive (BED) case. The operator factor for three different activities (road transport, charging and fieldwork) was varied from 0 (fully autonomous operation) to 1 (fully monitored operation). In the BED case, $O_r = 0.3$, $O_c = 0.1$, $O_f = 0.1$ (section 2.3.9) and $C_{AN} = 57{,}002$ € yr^{-1} (section 3.4.3).

Operator factor	0	0.5	1
Road transport (O_r)	−13%	+9%	+30%
Charging (O_c)	−2%	+7%	+15%
Fieldwork (O_f)	−8%	+12%	+32%
All ($O_r = O_c = O_f$)	−23%	+27%	+77%

3.6. *Case-based cost analysis*

Several other cases were simulated and their cost and active time requirement calculated. The different cases included the two different battery recharging methods described in Lagnelöv et al. (2020) and vehicles with larger batteries, multiple smaller batteries, high-powered chargers, lowered working time and autonomous diesel systems (Table 9).

Figure 10 shows the different annual costs for the different cases in Table 9. Notably, all but one of the electric cases had a cost comparable or lower than the manned diesel cases,

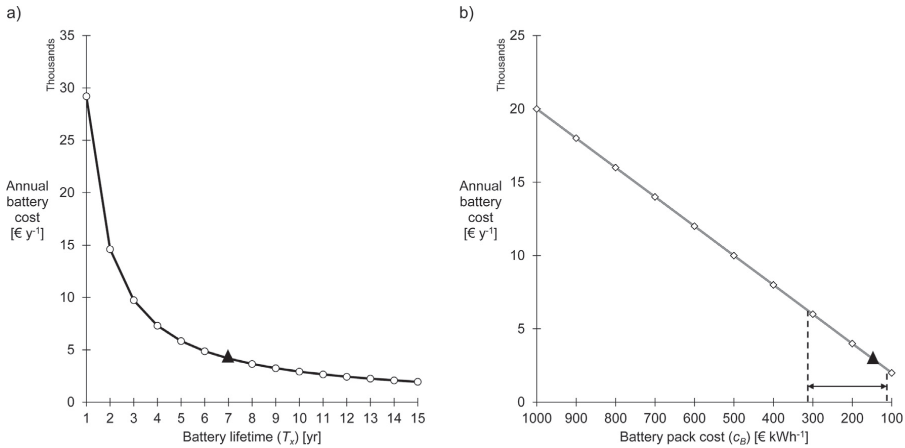

Fig. 9 – Impact on annual battery cost of a) battery lifetime before replacement and b) battery pack cost for the battery electric drive (BED) tractor case. The cost interval (dashed lines, arrow) from relevant literature is given (Comello & Reichelstein, 2019; McKerracher et al., 2020; Nykvist & Nilsson, 2015; Tsiropoulos et al., 2018). The values used in the BED case are shown as black triangles.

indicating that multiple system designs, charging systems and component sizes are competitive, even in the cases where the number of active days were higher.

In total, the autonomous diesel system (D2A) had the lowest annual cost and active number of days, indicating the high profitability of autonomy. A system with multiple smaller exchangeable batteries (BES2) had a significantly higher cost than the other BED systems, mostly due to a high number of active days, which led to high operator cost and timeliness cost. The system with four vehicles (NV4 BES) had the second lowest number of active days, but the third highest annual cost of the BED systems, due to its large investment cost and subsequent depreciation, as it provided expensive overcapacity.

For both conductive charging (CC) and BES, the systems with lowest total annual cost were those with large batteries (CC3 and BES3). This shows that the rate at which the battery ages is important, as the CC system with a higher powered charger, but one-third the energy content in batteries (CC2), had an annual battery cost that was more than seven times that of CC3, due to the rapid replacement of the batteries.

The BES studied had a lower number of yearly cycles per battery compared with CC, although they had similar total yearly cycles, as the yearly cycles were distributed on a higher number of batteries. This resulted in comparatively longer time to EOL for BES and gave a lower battery cost per kWh, even though the battery investment costs were higher (Fig. 10). All BED systems shown had lower yearly energy usage and cost compared with the diesel alternatives. Energy- and battery-related results for the different cases are shown in Table B1.

4. Discussion

4.1. *Battery ageing*

Battery ageing gave a large variation in MTTR between the different C-rates studied (Fig. 4). Increased rate of degradation with increased C-rate is discussed in the literature and linked to high cell temperatures, Li-plating on the negative electrode and electrolyte decomposition, which all lead to accelerated

Table 9 – Cases simulated in cost analysis. D = diesel, E = electricity, CC = conductive charging, BES = battery exchange system.

Case name	D1	D2	BED	D2A	CC 1	CC 2	CC 3	BES 2	BES 3	NV4 BES	BES 18 h
Fuel, Charging method	D	D	E/BES	D	E/CC	E/CC	E/CC	E/BES	E/BES	E/BES	E/BES
Number of vehicles (N_V)	1	2	2	2	2	2	2	2	2	4	2
Vehicle power (P_V, kW)	250	250	50	50	50	50	50	50	50	50	50
Battery energy eq. carried (E_B, kWh)	1315	1315	50	30,345	50	100	50	25	50	50	50
Number of extra batteries (N_B)	–	–	2	–	–	–	–	6	2	3	2
Charging power (P_C, kW)	30,345	30,345	50	1315	50	50	150	25	100	50	50
Number of chargers/fuel pumps (N_C)	1	1	1	1	1	1	1	2	2	3	1
Number of battery exchange stations (N_{BCS})	–	–	1	–	–	–	–	1	1	1	1
Daily working time (h, h d^{-1})	10	10	24	24	24	24	24	24	24	24	18

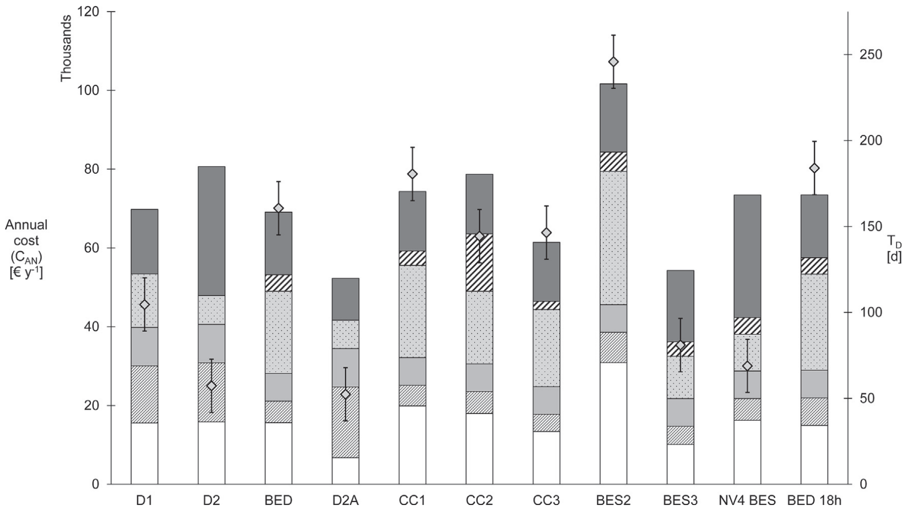

Fig. 10 – Average annual costs (bars, left axis) and active time (grey diamonds, right axis) for different cases. The annual costs are divided into costs for operator (white), fuel (thin diagonal stripes), maintenance (grey), timeliness (dotted on light grey background), battery (broad diagonal stripes) and annuity of investment (dark grey). The number of active days is shown, with error bars indicating one standard deviation.

ageing. In particular, high cell temperature is reported to be a major driver in battery ageing (Barré et al., 2013; Keyser et al., 2017; Tomaszewska et al., 2019; Uddin et al., 2016). However, Keyser et al. (2017) pointed out the difficulty in decoupling the effect of high C-rates from that of increased cell temperature in general, and the fact that different cell chemistries and designs respond differently to high C-rates. Because of this, it is difficult to compare the simulated results with literature values. However, for parameters described in this study, Keyser et al. (2017) gave a MTTR of 4–9 years for a NMC battery, depending on temperature, and de Hoog et al. (2017) showed a MCTR ranging from 1200 to 3500 cycles, which is similar to the results of this study. This indicates that the MCTR and MTTR used in this study are feasible, but further research is needed as data on the heavy duty off-road use of batteries is sparse.

By using the relationship shown in Fig. 9, the assumption of different lifetimes and the cost can be explored. As the relationship between annual cost and lifetime of the battery decreased exponentially, the most important consideration appears to be to increase the lifetime beyond the first years. In those intervals, the chosen C-rate was highly influential.

Battery size appeared to be of less importance than battery lifetime. However, the cases with larger batteries performed better than other changes in battery parameters (Fig. 10). They had a lower total annual cost and lower annual battery cost, even though their investment costs were higher. This was true for both CC and BES, with similar results. This seems to indicate that optimising the system for long-term battery use gives a better pay-off than investing in fast charging.

4.2. *Timeliness*

In previous studies (Magalhães et al., 2017; Moreda et al., 2016), it was assumed that a BED would suffer as regards capacity, due to the need for frequent recharging. This was encountered in the simulations made as the BED case had a 54% larger timeliness cost compared to D1. Inclusion of autonomy seemed to mitigate this, as BED still had a slightly lower annual cost. In addition, other cases were shown to have comparable or lower timeliness cost, indicating that with the right optimisation it is not an issue. Compared with other literature values, the resulting cost of timeliness appeared reasonable. Costs in the range 46–121 € ha^{-1} was shown for different cases with BED and 36–68 € ha^{-1} for the diesel cases. Gunnarsson and Hansson (2004) found a timeliness cost of 102 € ha^{-1} and de Toro (2005) a range of 30–145 € ha^{-1}, with an average of 60 € ha^{-1} for similar crops, conditions and climate. It is worth noting that harvest is included in both these ranges of values. However, as discussed in Lagnelöv et al. (2020), the number of workable hours in the field due to weather was lower in those studies than in other similar studies, which might explain part of the discrepancy.

The cost of timeliness is a theoretical comparison to an assumed optimal yield. As the sowing dates for BED would have been within the intervals shown by de Toro (2005); Witney (1988) and Myrbeck (1998), it is possible that the actual timeliness cost would have been lower than presented (Fig. 6). However, as it affected all cases equally, it still shows the dynamics of the concept. In addition, other climates and sites often have a wider window of suitable conditions, for example the UK (Witney, 1988), USA (ASAE, 2000; Edwards et al., 2016) and southern Europe (Savin et al., 2014). Since timeliness was not found to be an insurmountable part of the cost in the northern European climate in Sweden, it follows that this type of autonomous BED system would have a lower timeliness cost in those other regions, provided that the other parameters are similar.

4.3. Economics

For the BED case, part of the investment cost was for new infrastructure in the form of charging stations and battery changing stations, while all the infrastructure for the diesel cases was assumed to be in place, with no further need for improvement. This might appear to be an unfair comparison, but when trying to replace an existing solution it is a reality that the cost of new infrastructure must be included. Even with the installation of new infrastructure leading to a higher investment cost for BED compared with D1, the BED case had slightly lower annual costs thanks to the reduced operating costs, most notably fuel and maintenance. The annuity on investment was a relatively small part of the total annual costs, but the operating costs were of high significance (Fig. 8). For on-road vehicles, especially cars, the increased investment cost of BED vehicles is seen as a barrier to effective market penetration. For heavy duty vehicles this is a much less severe problem, as the vehicles in that market segment also have higher operating costs.

A high number of active days often involved a high cost, as it affected both timeliness (more delay) and operator costs (more hours where the vehicles must be monitored) (Fig. 10). In some exceptions, there was a trade-off with other costs, for example CC1 had a higher number of active days than CC2, but a lower cost due to the reduced battery cost. The number of active days could not be used on its own to draw conclusions on the annual cost of a system, but a high number of active days was often indicative of a system with poor optimisation, associated in turn with higher annual costs.

The actual cost of autonomous systems is difficult to determine correctly and only assumptions are possible without calculating the cost on component level, which was beyond the scope of this study. Instead, the investment cost of the autonomous system was included in the sensitivity analysis. The price of Robotti indicates that a tractor with a high level autonomy can be made for a similar price to manned tractor. Engström and Lagnelöv (2018) theorised that the removal of driver comfort systems and cabin could make for a cheaper vehicle and potentially make up for the increased cost of the autonomous system. The degree of automation is also important for the production cost of autonomous systems (Table 8). Marinoudi et al. (2019) found increased total costs at a certain level of automation for agricultural vehicles at which the component costs overtake the avoided labour cost and any further increase is economically sub-optimal. As the present study considered a highly autonomous system, it is possible that the cost of automation would have increased non-linearly and posed higher costs than presented here for highly autonomous solutions. However, unless exorbitantly expensive, it would be covered by the variations presented in the sensitivity analysis.

Fieldwork proved to be the operation for which a high degree of autonomy was most important, followed by road transport. The most time-consuming operation needed to have a high autonomy rate to have a low cost, which generally proved to be fieldwork and, for some BED cases, road transport. Road transport is a complex task to make autonomous, but there are indications that fieldwork is a more suitable task (Goense, 2005). Requiring the system to be monitored constantly ($O_{tot} = 1$) would increase the annual cost by 77%, making it more expensive than both the diesel cases studied here and generally economically unsuitable. This indicates that manned BED systems will struggle to compete in terms of costs with conventional diesel systems, whereas even partly autonomous systems may be competitive. This was somewhat explored with the BED 18 h-case, which showed a slight decrease in capacity but still had a comparable cost to the BED case with a 24-h working day, and the D1-case. It also highlights the benefit of understanding and minimising the number of hours of monitored non-productive work, most notably road transport. Due to more time spent refuelling and in transit the operator costs for BED and D1 was similar, which indicates an under capacity for the BED systems. Systems with higher battery capacity reduced the time spent in transit while having a slightly higher amount of time spent charging, which overall led to a low operator cost, notable in the CC3 and BES3 cases.

It is also worth discussing the manner in which the driver can be replaced. In this study, it was assumed that a single operator would monitor a certain fraction of the machine-hours. In reality, this function might hamper the vehicle's ability to work independently at all hours of the day, as the restrictions of human supervision would still be imposed, only at a higher level compared with a tractor driver's more direct involvement. The approach used in this study calculated the cost for every manned or monitored hour and other approaches would likely give different operator costs. Our approach was suitable for cost analysis, but there are many questions regarding general management that require further research.

4.4. Sensitivity analysis

The results from the sensitivity analysis showed that changes in the operating costs were more influential than changes in the investment costs, as the investments were distributed over the economic lifetime of the system, but changes in the operating costs were incurred directly. This indicates that in order to achieve a low annual cost, the operating costs need to be minimised and the economic lifetime maximised.

The case-based cost analysis (Fig. 10) showed the effects of different system design parameters, from large chargers to many small, replaceable batteries. The main dynamics discussed in (Lagnelöv et al., 2020) were confirmed, i.e. the difference between CC and BES was small but slightly favoured BES, $E_B < 50$ kWh led to a poorly optimised system; and a balanced ratio between battery size and charging speed is needed (here also shown as C-rate). It was also shown that cases with larger battery capacity (CC3 and BES3) had a noticeably lower annual cost compared to the diesel system, with BES3 having a comparable annual cost to D2A. This indicate that BED tractor systems can cost-effectively compete with manned and unmanned diesel systems. Additionally, the low costs obtained for most BED cases and the autonomous diesel system indicate that autonomy in an agricultural field setting can decrease the annual costs substantially.

5. Conclusions

In a simulated scenario, autonomous BED systems were found to have comparable or lower annual costs than equivalent cases with both one and two manned diesel vehicles. The BED systems had lower maintenance and fuel costs, but generally higher investment and timeliness costs and a higher number of required active days. The reduction in the operating costs outweighed the higher investment costs in the BED cases.

To ensure equal or comparable working rate to contemporary diesel systems, autonomy was shown to be necessary for the BED systems. The analysis revealed high sensitivity to degree of autonomy, with a fully monitored BED system having costs exceeding those of the diesel systems. Simulations of a diesel system running on the same assumptions as the BED systems (multiple smaller vehicles with a 24-h working day) showed low cost and high capacity, indicating the advantages of autonomy. These findings indicate that many of the predicted problems with agricultural field BEVs are solvable or can be mitigated by vehicular autonomy. In addition, this study showed that the cost of timeliness was generally larger for BED systems than for diesel systems but still resulted in a lower annual cost due to savings in operational costs.

The increased investment costs associated with BEVs proved to be a small proportion of the total annual costs of operation. Battery ageing had a significant impact on the associated costs, but using batteries larger than 50 kWh or multiple batteries extended the lifetime of the batteries significantly. In addition, it was shown that the operating costs of the vehicle systems were more influential than the investment costs. Cases that ensured low operating costs through reduced maintenance, fuel, timeliness and operator costs had lower annual costs.

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.

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Appendix A. Battery model simulation parameters

Table A1 – Simulation and modelling parameters used in simulation of battery ageing

Parameter [unit]	Variable	Value
Ageing parameter	alpha	0.67
Surface area	Av_neg	3*0.384/rp_neg
Bruggeman coefficient for tortuosity in positive electrode	brugl_pos	2.98
Bruggeman coefficient for tortuosity in separator	brugl_sep	3.15
Initial electrolyte salt concentration [mol m^{-3}]	cl_0	1200
[mol m^{-3}]	cs_pos_max	48,000
Initial SEI layer thickness [mm]	dfilm_0	1
Maximum cell voltage [V]	E_max	4.1
Minimum cell voltage [V]	E_min	2.5
Electrolyte phase volume fraction negative electrode	epsl_neg	0.444
Electrolyte phase volume fraction positive electrode	epsl_pos	0.41
Electrolyte phase volume fraction separator	epsl_sep	0.37
Solid phase volume fraction negative electrode	epss_neg	1-epsl_neg-0.172
Solid phase volume fraction positive electrode	epss_pos	1-epsl_pos-0.170

(continued on next page)

Table A1 – (continued)

Parameter [unit]	Variable	Value
Ageing parameter [s^{-1}]	f	2.0e2
Ageing parameter	H	6.7
1C discharge current [m^2/3600s]	i_1C	Q0*1
Constant current, charge	I_ch	i_1C
Constant current, discharge	I_dch	-i_1C
Minimum cell current for constant voltage charge	I_min_ch	i_1C/20
Ageing parameter [h]	i1C_loc	Q0/(Av_neg*L_neg)/1
Ageing parameter	J	8.40e-04
Reaction rate coefficient negative electrode [m s^{-1}]	k_neg	2e-11
Reaction rate coefficient positive electrode [m s^{-1}]	k_pos	5e-10
SEI layer conductivity [S m^{-1}]	kappa_film	5e-6
Length of negative electrode [m]	L_neg	55e-6
Length of positive electrode [m]	L_pos	40e-6
Length of separator [m]	L_sep	30e-6
Molar mass of product of side reaction [kg mol^{-1}]	M_sei	0.16
Number of cycles	no_cycles	2000*2 + 80
Initial capacity	Q0	cs_pos_max*(1–0.25)*epss_pos*L_pos*F_const
Density of product of side reaction [kg m^{-3}]	rho_sei	1.6e3
Particle radius negative electrode [m]	rp_neg	2.50e-6
Particle radius positive electrode [m]	rp_pos	0.25e-6
Cell temperature [°C]	T	20
Approximative total cycling time	t_cycling	(no_cycles+1)*10000/t_factor
Time acceleration factor	t_factor	80

Appendix B. Case-based detailed results

Table B1 – Energy and battery results from the case study. Battery lifetimes longer than the simulated 11 years are denoted 11+. The results from the BES18h case were omitted, as the case is a variant of the BED case.

Case name	C-rate	E_{tot} [kWh y^{-1}]	Energy cost [€ y^{-1}]	Eq. cycles [y^{-1}]	Eq. cycles per battery [y^{-1}]	MCTR (calculated)	MTTR [y]	Battery investment cost [€]	Battery cost per cycle [€][b]	Battery cost per kWh (over lifetime) [€]
D1	–	168,748	14,512	243[a]	–	–	–	–	–	–
D2	–	174,294	14,989	218[a]	–	–	–	–	–	–
BED	1C	91,462	7317	2464	616	4,24	6.9	29,200	6.8	0.17
D2A	–	208,994	17,973	229[a]	–	–	–	–	–	–
CC 1	1C	88,636	7091	2432	1216	4,24	3.5	14,600	3.0	0.08
CC 2	4C	93,384	7471	2554	1277	1,2	0.9	14,600	11.4	0.29
CC 3	C/10	73,069	5846	741	370	7,76	11+	43,800	5.6	0.05
BES 2	1C	116,966	9357	5834	729	4,24	5.8	29,200	6.7	0.33
BES 3	1C	79,302	6344	1,09	272	4,24	11+	58,400	13.4	0.17
NV4 BES	1C	95,766	7661	2544	363	4,24	11+	51,100	11.7	0.29
BES 18H	1C	87,616	7009	2354	588	4,24	7.2	29,200	6.2	0.16

[a]For diesel systems, the term “cycling” is best replaced with “refuellings.”
[b]Calculated on the annuity cost of batteries and yearly cycles per battery.

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Life Cycle Assessment of Autonomous Electric Field Tractors in Swedish Agriculture

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Abstract: There is an increased interest for battery electric vehicles in multiple sectors, including agriculture. The potential for lowered environmental impact is one of the key factors, but there exists a knowledge gap between the environmental impact of on-road vehicles and agricultural work machinery. In this study, a life cycle assessment was performed on two smaller, self-driving battery electric tractors, and the results were compared to those of a conventional tractor for eleven midpoint characterisation factors, three damage categories and one weighted single score. The results showed that compared to the conventional tractor, the battery electric tractor had a higher impact in all categories during the production phase, with battery production being a majority contributor. However, over the entire life cycle, it had a lower impact in the weighted single score (−72%) and all three damage categories; human health (−74%), ecosystem impact (−47%) and resource scarcity (−67%). The global warming potential over the life cycle of the battery electric tractor was 102 kg CO_2eq.ha^{-1} y^{-1} compared to 293 kg CO_2eq.ha^{-1} y^{-1} for the conventional system. For the global warming potential category, the life cycle of the use phase was the most influential and the fuel used was the single most important factor.

Keywords: life cycle assessment; battery electric vehicle; tractors; environmental impact; agriculture

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1. Introduction

According to IPCC [1], reaching net-zero emissions of greenhouse gases (GHG) is required in order to limit and stabilise human-induced global temperature increase. To limit global warming to 1.5 °C above pre-industrial levels, the global carbon budget (amount of CO_2eq. that can be emitted before that temperature is reached) must be kept between 300 and 900 $GtCO_2$ [1]. Globally, agriculture has a major impact on emissions of GHG. In 2010, 21–24% (9.5–11.9 Gt $CO_{2\,eq.}$ y^{-1}) of global GHG emissions originated from the AFOL (agriculture, forestry and other land use) sector [2,3]. Of this, roughly half was attributable to agricultural production, and 0.4–0.6 Gt $CO_{2\,eq.}$ y^{-1} of that to agricultural machinery use. To reach the net-zero emissions goal, agriculture cannot be ignored and environmentally friendly solutions for agriculture are needed.

The European Union (EU) has set the goal of being carbon net neutral by 2050 [4]. The Swedish government has established similar goals, i.e., to have a fossil-free vehicle fleet by 2030 and to be carbon net neutral by 2045 [5]. This includes areas that have traditionally been difficult to shift from diesel to renewables, such as agriculture, forestry and mobile work machinery. These sectors place high demands on their vehicles, so robust, cost-effective solutions are needed. One such solution is implementation of battery electric vehicles (BEV), for both on-road and nonroad vehicles, using electricity from fossil-free sources. However, automotive batteries have been shown to have a large environmental impact during their production [6–8], although EVs have also been shown to have a lower impact during the use phase due to higher driveline efficiency and lower fuel impact [9,10]. In the agriculture sector, multiple research projects and demonstrations of BEVs for field work have been conducted, with promising results [11–15]. It has therefore been concluded by the World Economic Forum [16] that electrification is a potentially cost-effective way of reducing GHG emissions in agriculture. There is significant interest from policy makers in a more renewable food production system.

In previous studies by our research group assessing the production capacity and economic impact of autonomous battery electric tractors through simulations [17,18], they were shown to have a comparable work rate and lower total annual costs for certain system topographies. One of the main arguments for changing from a few large diesel-powered tractors to multiple smaller battery electric tractors is the potential environmental benefit in replacing diesel with electricity that has a smaller environmental footprint. For this change to be feasible, we have shown that autonomous operation is a prerequisite, due to economic factors [18]. While a multitude of environmental impact assessments and life cycle assessments (LCAs) have been performed for agricultural machinery [19–21], Li-ion batteries [6,7,22,23], components in the electric driveline [24,25] and on on-road BEVs [9,26], there is a lack of LCAs on electric tractors and other electric mobile work machinery.

Many studies look exclusively at the climate impact in the form of GHG emissions when performing an LCA, but several other impact categories are of interest in order to obtain a more complete understanding of the impacts of a system. In a review of existing LCAs on automotive batteries by Aichberger and Jungmeier [8], one of the main conclusions was that inclusion of more impact categories than GHG and energy use is recommended for LCAs concerning automotive batteries, as also stated by Loon, et al. [27]. For example, availability of key materials and resource scarcity are potential challenges connected with automotive batteries [6]. Arvidsson et al. [28] recommend the use of several impact factors in LCA of emerging technologies because new technologies may lead to different environmental impacts than the systems they replace. In LCAs of agricultural systems, several other impact categories are of interest, notably eutrophication of freshwater and the effect on biodiversity. By combined studies of impact factors for agriculture and BEVs, a more thorough understanding of the environmental impact of battery electric field machinery can be gained, and a more informed comparison to the systems used today can be made.

The aim of the LCA performed in this study was to determine the environmental impact of a self-driving BEV tractor system and compare it with that of a contemporary diesel tractor system for a Swedish grain farm. The hypothesis tested was that changing to an electricity-based system leads to lower environmental impacts.

2. Materials and Methods

2.1. Goal and Scope

This LCA study assessed the potential environmental impact of an autonomous BEV agricultural vehicle system and compared it with the impact of a conventional internal combustion engine (ICE) diesel-powered system used today. The environmental impact was represented by characterisation of several midpoint and endpoint impact categories, damage assessment and a weighted single score, as explained in further detail in Section 2.5. As midpoint impact categories can be used as a measure of emission intensity, and endpoint impact categories as a measure of the resulting impact on human health and the environment [29], determining both gives a broader picture of a system's impact.

The scope of the LCA was limited to production and assembly, use phase and end-of-life of two small BEV agricultural field tractors, as described in Section 2.1. Comparisons were made between a vehicle system consisting of these vehicles and a vehicle system consisting of a conventional manned diesel-powered tractor. A full cradle-to-grave (CTG) analysis was made, and the gate-to-gate (GTG) aspect was also assessed separately.

The tractors were assumed to be used on a Swedish grain farm of 200 ha growing winter wheat, spring wheat, barley and oats, in the manner described in Lagnelöv, Larsson, Nilsson, Larsolle and Hansson [17]. The LCA methodology presented in the ISO 14040:2006 standard [30] was used, together with scalable life cycle inventories (LCIs) for the vehicle glider, the battery and the driveline. LCIs for conventional tractors, electric vehicles and trucks were used, due to data shortages. As the focus of the study was on the impact of the machine system and on comparison with the systems used today, original LCIs for components were not created and secondary sources were used when possible, after verification.

To account for the emerging state of the technology studied, a process-based, consequential LCA was performed to test the hypothesis that a system of autonomous BEVs reduces the climate impact in agricultural machinery systems compared with a contemporary diesel tractor system doing the same work under the same conditions.

Vehicle Definitions, System Boundary and Functional Unit

The BEV system analysed consisted of two autonomous tractors with 50 kW permanent magnet synchronous machine (PMSM) electric motors and 100 kWh nickel cobalt aluminium (NCA) Li-ion batteries. Each vehicle had one on-board battery and an additional battery for rapid battery replacement, making a total of four 100 kWh NCA batteries (two per vehicle). Because the vehicles were assumed to be autonomous, it was assumed that they had no cabin. This vehicle system has been shown in previous studies to have a high theoretical work rate [17] and to compare favourably to contemporary tractor systems in economic terms [18]. The infrastructure necessary for charging the vehicle system was also included in the analysis. It comprised two 50 kW CC/CV DC chargers and a battery exchange system.

As the reference case, a 250 kW contemporary diesel tractor was assessed using the same methods and models. Production, fuel, repair, maintenance and end-of-life steps were included in the life cycle of the conventional vehicles and in that of the BEV vehicles.

The system boundary of the study started at manufacturing of the main vehicle components and ended after the end-of-life phase, as shown in Figure 1. As the focus of the study was on machinery, the agricultural part of the use phase was not modelled other than in terms of energy demand [18], as it was assumed to be similar for the cases studied. In addition, the autonomous system only included the hardware on the vehicle and a single base station, while any additional infrastructure was not included.

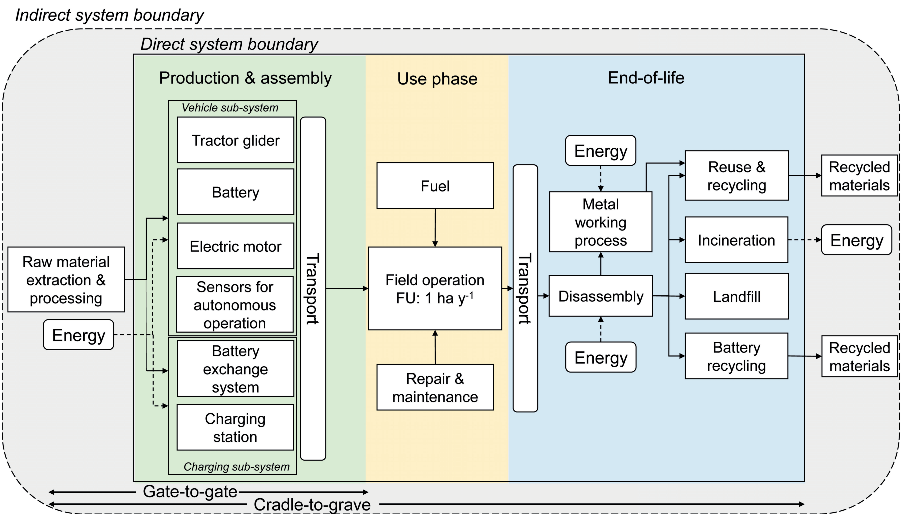

Figure 1. System boundary of the studied system. Direct system boundary (square) shows the system described in the article—production & assembly (green), use phase (yellow) and end-of-life (blue). The indirect system boundary (dashed border rounded square) shows processes that are not specifically studied or described, but are included in the result. The functional unit (FU) is included, and energy flows are represented by dashed arrows.

The functional unit was set as one average hectare of arable land growing cereal, as defined and with the machinery operations simulated and cereal data used in Lagnelöv, Larsson, Nilsson, Larsolle and Hansson [17] during an average year, giving a functional unit of 1 ha^{-1} y^{-1}.

2.2. Inventory Analysis

Inventory data for autonomous vehicles are sparse, and data for tractors are less available than data for on-road heavy duty vehicles. It was assumed that data from other vehicles can be scaled, adjusted and fitted to the autonomous system, mostly concerning electrification and autonomisation of vehicles (Table 1). The inventory and subsequent analysis were made in the LCA software SimaPro (v.9.0.0.49, PRé sustainability, Amersfoort, The Netherlands) [31]. A complete inventory list can be found in Supplementary Material S1.

Table 1. Components included in life cycle assessment (LCA) of the battery electric vehicle (BEV) and internal combustion engine (ICE) cases. Categories marked with * were included, but to a reduced extent. Dataset names and complete inventory list can be found in Supplementary Material S1.

Phase	Category	Component	BEV	ICE	Main Sources
Manufacturing and assembly	Glider	Cab		X	[32,33]
		Tyres and wheels	X	X	[32,33]
		Frame	X	X	[32,33]
		Chassis	X	X	[32,33]
	Driveline	Lead-acid battery		X	[33]
		Engine		X	[33]
		Diesel tank		X	[33]
		Transmission	X *	X	[32,33]
		Auxiliary fluids (engine oil, AdBlue etc.)		X	[33]
		Li-ion battery	X		[34]
		Electric motor (PMSM †)	X		[35]
	Other components	Autonomous system and sensors	X		See Section 2.2.6
	Infrastructure	Electric charger	X		[36]
		Battery exchange system	X		[37,38]
Use phase	Fuel	Diesel		X	[39]
		Electricity	X		[40–42]
	Repair and maintenance	Repair	X	X	[33,43]
		Maintenance	X *	X	[33]
End-of-life	Disposal	Vehicle disposal	X	X	[27,33,44]
		Charging infrastructure disposal	X		[27,33]
	Recycling	Battery recycling	X		[45]

† Permanent magnet synchronous machine.

Transport in the inventory was divided between freight shipping and road transport. The road transport was assumed to be perfomed by truck or lorry in the 16–32 tonnage interval and with a Euro 6 emission standard because it is the most common truck used in Sweden and is also common in Europe according to logistics experts (A. Lagnelöv, J. Peterson & C. Brus, VDAB, Uppsala, Sweden, Personal communication 2021-04-08).

2.2.1. Glider

The inventory for the glider and other nondriveline parts of the vehicle can be found in several publications. Wolff, Seidenfus, Gordon, Álvarez, Kalt and Lienkamp [32] give an inventory for a general heavy-duty vehicle, while Lee, et al. [46] and Mantoam, Romanelli and Gimenez [20] focus on agricultural tractors. However, their inventories include the cabin and the conventional driveline, neither of which was included for the autonomous battery electric drive (BED) tractors in this study. According to Nemecek and Kägi [33], on-road heavy duty vehicles like lorries can be used as an approximation for material composition and assembly of tractors where other data sources cannot be found. Because the data in Wolff, Seidenfus, Gordon, Álvarez, Kalt and Lienkamp [32] are separated into machine parts and are scalable, they were selected for use. A glider without internal combustion engine (ICE) and cab was constructed and scaled to a total glider weight of 2500 kg, giving a scaling factor of 63.5% compared to the source data.

2.2.2. Battery

The battery considered in Lagnelöv, Dhillon, Larsson, Nilsson, Larsolle and Hansson [18] was a Li-ion battery with an NCA positive electrode ($LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$) and graphite as the negative electrode (NCA-C). Inventory data for a NCA-C battery module taken from Le Varlet, Schmidt, Gambhir, Few and Staffel [34] were used to represent this battery. Some materials were not found in the database, so recommended proxies listed in Siret, Tytgat, Ebert, Mistry, Thirlaway, Schultz, Xhantopoulos, Wiaux, Chanson, Tomboy, Pettit, Gediga, Bonell and Carrillo [45] were used. In addition, the electricity used for battery assembly and some manufacturing was switched from Norwegian mix in the original article to Swedish mix, due to the focus of the present study being the Swedish context, but component manufacturing was assumed to use either local or Chinese electricity mix [34,40].

It is worth noting that the inventory in Le Varlet, Schmidt, Gambhir, Few and Staffel [34] is for residential batteries for local energy storage, which is a different use from that of electromobility. However, the inventory data were based on batteries for use in electric vehicles [9,47–50] and were therefore considered applicable. Because the battery studied in Lagnelöv, Dhillon, Larsson, Nilsson, Larsolle and Hansson [18] was specified in terms of energy content (in kWh) and the battery LCI was given in mass units, a gravimetric energy content of 0.10 Wh g^{-1} taken from Le Varlet, Schmidt, Gambhir, Few and Staffel [34] was assumed.

2.2.3. Battery Recycling

Standardised general invenory data for battery recycling, including resource use and credits, are provided as part of the EU product environmental footprint (PEF) documentation for batteries in mobile applications (PEFCR) [45]. The PEFCR data cover the broader-term Li-ion battery but are modelled specifically on LCO, NMC, LFP and Li-Mn chemistries. It was assumed that this was an adequate stand-in for the recycling part of the chemistries (NCA-based) used in the model in this study. Recycled materials were used as credits and replaced virgin material in applications outside the system boundry, modelled as a negative flow.

2.2.4. Electric Motor

A gate-to-gate LCI for a general PMSM electric motor of variable power and torque was performed by [51], with additional data given in [35]. It details the production of the motor, but not the rest of the driveline. End-of-life is also omitted. However, this still served as a good base for the electric machines used in the driveline in the present assessment, as PMSM is the most common electric motor technology used in electric vehicles [51] and the resolution is high. This value was verified with values for an electric motor of the same power presented in Spielmann, et al. [52], which, due to lower resolution, had lower impacts but agreed on the key impact points and impact magnitudes.

2.2.5. ICE Driveline

The conventional tractor used for comparison was assumed to be a 250 kW tractor, using field tractor data from Nemecek and Kägi [33]. This included raw material extraction, manufacturing, assembly, maintenance and disposal steps of the life cycle. However, these factors are often aggregated to the manufacturing phase in the presentation of results in this paper. The model used the tractor mass as a quantifying unit for the inventory. The unloaded weight was assumed to be 10,800 kg, which was based on the average weight of modern tractor models with approximate power 250 kW (Valtra S294, Fendt 933 Vario, John Deere 7R330). The mass and inventory data were verified with data taken from [20] for a 246 kW tractor with mass 10,950 kg. The exact composition tends to vary between data sources, but steel and ductile iron are key components, with rubber (in the form of tyres) and oil frequently cited as a large part of the maintenance materials used [20,32,33,46]. A comparison of key materials from different sources by weight can be seen in Figure 2.

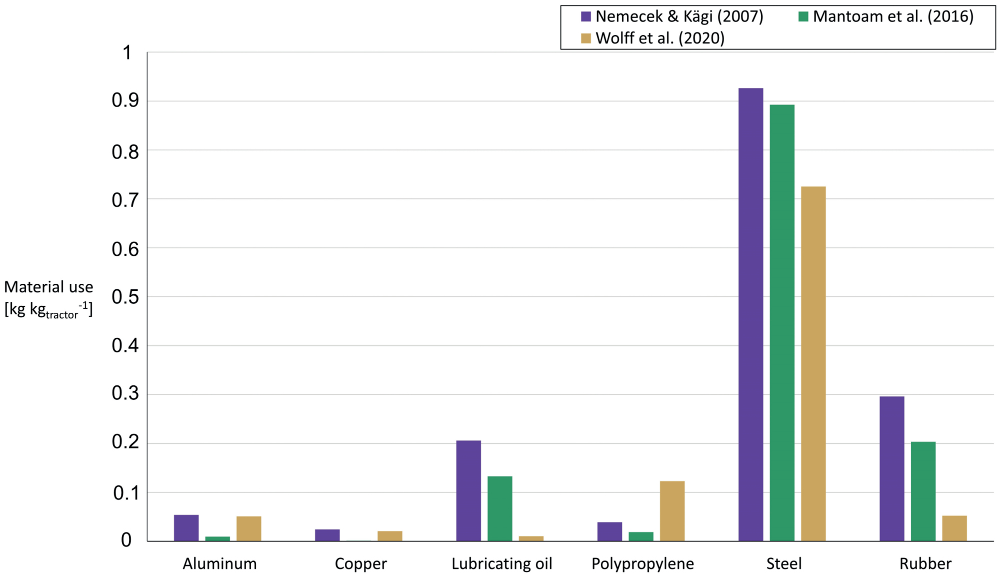

Figure 2. Material use in the assembly and maintenance phases of the vehicle body for key materials by weight [20,32,33]. Note that the data from Wolff, Seidenfus, Gordon, Álvarez, Kalt and Lienkamp [32] do not include maintenance and repairs, and hence the usage of steel, rubber and lubricating oils is lower than in the other sources.

2.2.6. Autonomous System and Sensors

Because there are no industry standards for the equipment used for self-driving vehicles, information on the components in these vehicles was gathered from previous studies and industry practitioners. The sensors listed in Table 2 represent a realistic setup according to industry experts (L. Ahlman (Agrodroids), F. Löfgren (Dynorobot), A. Stålring & F. Gradelius (Tegbot), Linköping, Sweden, Personal communications). This is in line with the technology recommendations in Mousazadeh [53], Hirz and Walzel [54].

Table 2. Type and number of sensors and components used to represent the autonomous capacity of the vehicle system.

Component	Weight (kg)	Number of Components	Model Example
Lidar	2.2	4	Sick MRS6124R-131001
GPS	0.5	1	
Camera	0.037	3	Point Grey Firefly MV 0.3 MP Color USB 2.0 Research Camera
Radar	1.08	2	Sick RAS407-2801100
Wifi/5g router	0.23	1	Sick TDC-E200R6
Base station	0.23	1	
GPU	0.25	1	Nvidia Jetson
Various sensors	0.1	6	Temperature, rainfall, gyro, air moisture, rotation counter and position sensors
Switch	0.5	1	
Control unit	0.5	1	
Copper wiring	0.2 m	19	

Due to the lack of detailed inventory data and the assumption that the sensors make up a small part of the total impact, proxies were used where applicable. It was assumed that all the basic sensors weighed 0.1 kg and consisted of equal ratios of active and passive electronic components, with a wiring board making up half the total weight. Lidar, radar, cameras, GPS units and routers were assumed to make up half the weight in the plastic casing, with half of the remainder being wiring board. The remaining quarter was equally distributed on passive and active electronics components. Each component was assumed to require 20 cm of copper wiring for data and electricity transmission, at a weight of 0.045 kg m^{-1}. A switch and control unit electronics were assumed to be needed.

2.3. Use Phase

2.3.1. Refueling Infrastructure

The LCI for the charging infrastructure was taken from Lucas, Silva and Neto [36] and included two fast chargers (50 kW DC-DC) and two slow chargers (3 kW) for less demanding charging during longer periods of vehicle downtime. Both chargers were assumed to be located on the farm and grouped at two stations, each containing one 50 kW and one 3 kW charger. In addition, it was assumed that 10 m^3 of soil had to be excavated and that 1 m^3 of concrete was used for the foundation for each fast charger, which is in line with values presented in Lucas, Silva and Neto [36].

The BEV system also requires a battery exchange system. Due to lack of existing systems of the correct size, a 42-inch forklift automatic transfer carriage (ATC) with a gross weight of 349 kg [37] was assumed. It was made of a steel frame including 10 steel rollers and was modelled as a general steel product with a minor hydraulic system. It was assumed to function using the motor and battery of an existing electric hand pallet truck, which was modeled after a Toyota LWE200 electric pallet truck using the option to exchange the battery pack to Li-ion, giving it a total weight of 374 kg [38].

It was assumed that a diesel fuel tank and a fuel pump were part of the existing infrastructure on the farm because they are common equipment and often display a lifetime longer than the vehicle itself.

2.3.2. Fuel

The amounts of fuel used were taken from Lagnelöv, Larsson, Nilsson, Larsolle and Hansson [17] and amounted to an average of 79,302 kWh y^{-1} electricity for the BEV and 168,748 kWh y^{-1} in diesel for the conventional machine over the vehicle's lifetimes of 15 years.

The electricity used as fuel for the BEV was Swedish marginal electricity, a mix consisting of 41.4% imported electricity produced from natural gas, 35.1% from wind power and 23.5% from biomass in the form of wood products [40]. The origin of the electricity used was varied in scenario analysis (see Section 3.3) to provide a thorough view of the impacts of different mixes because the choice of electricity is reported to be one of the most impactful assumptions in LCA of EVs [10,55].

Emissions from the diesel used as fuel for the conventional machine in this study were based on emissions from burning diesel in agricultural machinery [39]. There is a legal requirement for a blend with renewable fuels in Sweden, but pure diesel was used as the default case, with renewable fuel additives included in the scenario analysis in Section 3.3.

2.3.3. Maintenance and Repair

It was assumed that repair and maintenance of the BEV followed the guidelines for agricultural machinery [20,33,43]. However, engine oil, AdBlue and some lubricants were ignored because they are not utilised in EVs. It was assumed that for every kg of tractor, 0.176 kg tyres and 0.103 kg of hydraulic oil were needed during the use phase [33], as well as 27.2 MJ per kg material used. To account for repairs during the vehicle's lifetime, a repair factor of 0.2 was used, meaning that 20% of the initial material in the tractor needed replacing during use [33]. This was handled by scaling up the glider by 20% because the motor and charging infrastructure were assumed to last the lifetime of the tractor without repairs and the battery was replaced instead of being repaired. This meant a total glider scaling of 76.1% compared to the data in [32]. These values were verified with data from [20,43].

2.3.4. Battery Replacement

The batteries assumed in the system are replaced as soon as their maximum state-of-charge reaches 0.8 of the initial maximum value at full charge (this is sometimes called a state-of-health of 0.8). This happens at different equivalent full cycles depending on the charging speed. For the given charging rate, charging speed and battery size, the lifetime of the battery was simulated to exceed 4000 cycles and was theoretically calculated to be 15.5 years [18]. However, calender ageing was not included and the charging rate was assumed to be the primary driver behind cell ageing. To include the uncertainties in the battery simulations, variations in the battery lifetime were included in the sensitivity analysis in Section 3.3.

2.4. *End-of-Life*

The end-of-life stage is reported to be the stage with the lowest life cycle emissions for electric vehicles, when viewed in isolation [27]. It is also a stage that has high uncertainty for EVs and is often simplified or omitted in studies of EVs [56]. Therefore, a simple method in line with previous work on EVs [27,45] and agricultural machinery [33] was adopted. The battery was assumed to be disposed of as recommended by Siret, Tytgat, Ebert, Mistry, Thirlaway, Schultz, Xhantopoulos, Wiaux, Chanson, Tomboy, Pettit, Gediga, Bonell and Carrillo [45], adjusted with battery production data from [34] to eliminate recycling of materials not used in the production.

Following the suggestions of Loon, Olsson and Klintbom [27] and Nemecek and Kägi [33], it was assumed that for the rest of the vehicle, the main metals (aluminium, copper and steel) were recycled to 100%. To obtain a realistic energy demand, it was assumed that the metals needed to go through a process before reuse. This was characterised by the average metal working processes for each of the main metals and a general metal working process for remaining metals, described by Steiner and Frischknecht [57].

The rubber in the tyres was assumed to be used for energy recovery. Oils were assumed to be incinerated in hazardous waste incineration plants, while paper, plastics and rubber were assumed to be incinerated for energy recovery and glass was assumed to be sent to landfill [9,27]. The energy use for disassembly and shredding was set at

139 kWh/ton machinery, based on Nemecek and Kägi [33]. All components were assumed to be disposed of within Sweden and transported 150 km by lorry, a value used by Loon, Olsson and Klintbom [27]. The same assumptions were made for recycling of refuelling and recharging infrastructure. In addition, the concrete used for the foundation was assumed to be sent to landfill for disposal. Recycling opportunities for concrete exist but are not commonly used globally. The waste treatment allocation can be seen in Table 3.

Table 3. Waste treatment scenario allocation for each major component category, in mass fractions and with the total weight scaled as described in Sections 2.2.1 and 2.3.3. Battery recycled as detailed in Siret, Tytgat, Ebert, Mistry, Thirlaway, Schultz, Xhantopoulos, Wiaux, Chanson, Tomboy, Pettit, Gediga, Bonell and Carrillo [45].

Tractor Part	Sub-Part	Reuse/Recycling (%)	Landfill (%)	Incineration (%)	Hazardous Material, Incineration (%)	Weight (kg)
Glider	Frame	100	0	0	0	650
	Chassis	97	0	3	0	1218
	Tyres and wheel	67	0	33	0	503
	Other components	51	0	46	4	629
	Glider total	83	0	16	1	3000
Motor	PMSM † motor	83	2	7	7	26.9
Charger	Charger	14	73	13	0	3305
Battery exchange system	Body	99.7	0	0.3	0	349
	Pallet truck	95	0	3	1	374

† Permanent magnet synchronous machine.

2.5. Impact Assessment (LCIA)

The most common impact assessment categories presented in previous LCAs on EVs, automotive batteries and agricultural field operations were compiled [9,20,25,27,45–47,50,58,59]. This was done to encompass the scope of both the EV and agricultural viewpoints. A summary of the compilation can be seen in Table S3a in the Supplementary Material. The chosen impact factors (Table S3b in the Supplementary Material) were also in line with recommendations made by Loon, Olsson and Klintbom [27]. The most frequently used impact category factors were then matched with the factors given in the ReCiPe method [60]. This resulted in 11 out of 18 midpoint characterisation categories from SimaPro being used. When calculating damage assessment and single score value, all 18 original categories were included so as not to undermine the original method [31] or introduce bias (Figure 3).

The perspective chosen decides the weight of impacts and the conversion factors used. The hierarchist perspective was stated as the default perspective [60] and was used in this study. Results for both midpoint and endpoint indicators are presented, with the conversion factors in Table S3c in the Supplementary Material used to go from midpoint to endpoint, according to this equation:

$$CFe_{x,c,a} = CFm_{x,c} \times F_{M\rightarrow E,c,a} \quad (1)$$

where CFe is the endpoint characterisation factor, CFm is the midpoint characterisation factor, c is the perspective (in this study hierarchist), a is the area of protection (human health, ecosystems, resource scarcity), x is the stressor and $F_{M\rightarrow E,c,a}$ is the midpoint-to-endpoint conversion factor for perspective c and area of protection a [60].

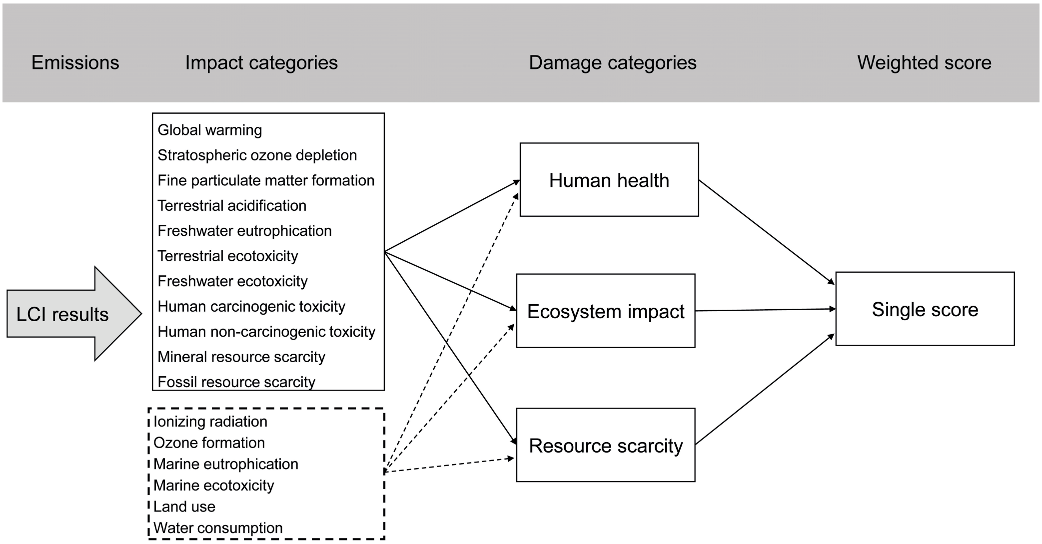

Figure 3. Life cycle impact assessment (LCIA) framework used in this study with all impact categories shown, divided between those that are individually presented (full box) and those included in the damage assessment and weighted score, but not presented separately (dashed box).

3. Results

3.1. Results for the BEV System

3.1.1. GTG

A GTG impact distribution for the battery electric tractor system can be seen in Figure 4. For all impact categories apart from stratospheric ozone depletion, the battery constituted the majority of the impacts, ranging from 42 to 83% of the gate-to-gate impacts. Other notable components with high impacts were the glider and the chargers. They included many metals, processes and weight, which in the cases translated to high impacts, especially as the charger infrastructure was slightly oversized. Autonomous sensors, although comprising a very small fraction of the total weight, had a relatively high impact. The motor, despite including rare earth metals, had a small impact in all categories compared with the other components.

Because the battery constituted a majority of the impact in most cases, the results of the battery inventory and impact assessment are shown in Figure 5. The material composition showed a roughly equal distribution of metals, with lithium and cobalt being less common by weight than aluminium, copper, nickel and steel. Graphite and the electrolyte both constituted 13% of the weight. The electrodes constituted 49% of the weight and 43% of the global warming potential (GWP). The components made mostly from metal, mainly BMS and module casing, also had a sizeable impact on the climate impact. In the functional unit, the climate impact for the GTG, or manufacturing, phase resulted in 34 kg CO_2eq.ha^{-1} y^{-1} in total, of which the battery contributed 21 kg CO_2eq.ha^{-1} y^{-1} or 62%.

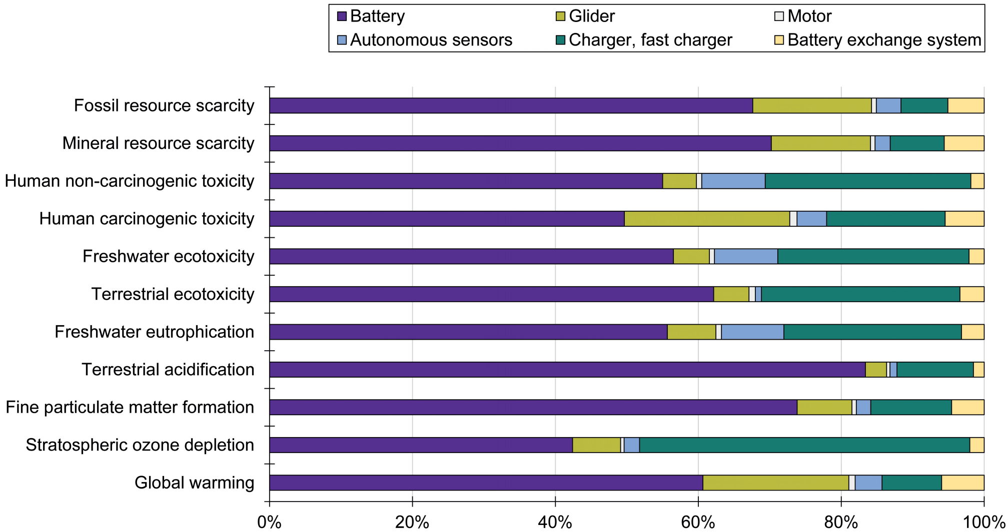

Figure 4. Gate-to-gate (GTG) impact distribution using midpoint indicators for the battery electric vehicle (BEV) tractor system, including infrastructure. The most commonly used impact categories are shown. "Glider" includes frame, chassis, tyres and wheels, other components and glider assembly.

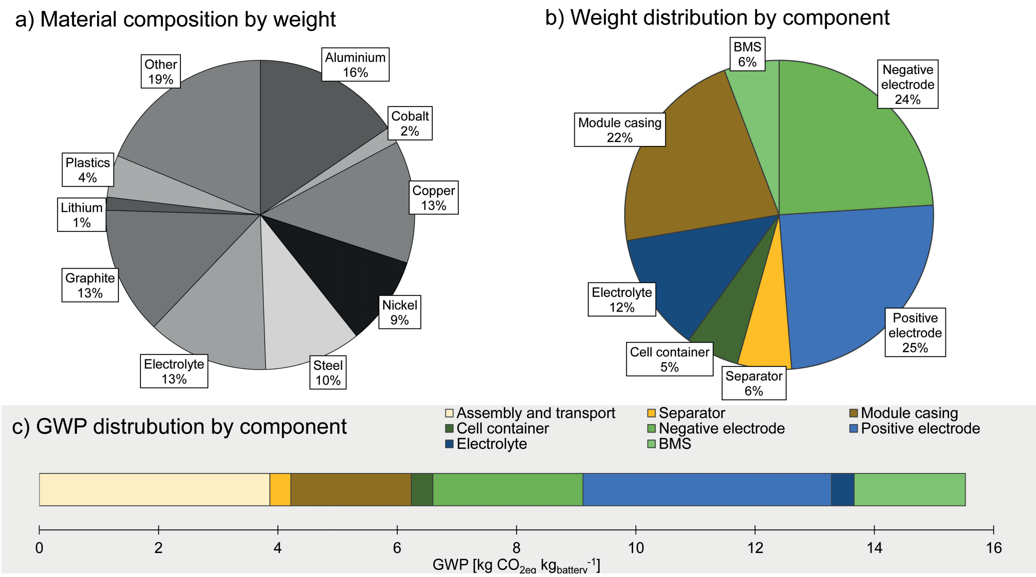

Figure 5. Weight distribution for the nickel cobalt aluminium-graphite electrode (NCA-C) battery module by (**a**) material (**b**) and component, and (**c**) the global warming potential (GWP) impact by component.

3.1.2. Cradle-to-Grave

The results of the CTG analysis showed that for all impact categories studied, the manufacturing of the batteries and the electricity used as fuel were responsible for the majority of the impacts (Figure 6). This indicates the need to focus on these parts when analysing the overall impact of the system. The impact factors concerning mineral resource scarcity, human toxicity, ecotoxicity, eutrophication and acidification comprised most of the impact from battery manufacturing. The remaining categories, mainly global warming, ozone depletion and fossil resource scarcity, comprised most of the impact from electricity use (66–71%). Apart from these, the highest impact was generally seen for the charger infrastructure and glider manufacturing. The full results can be seen in Supplementary Material S2.

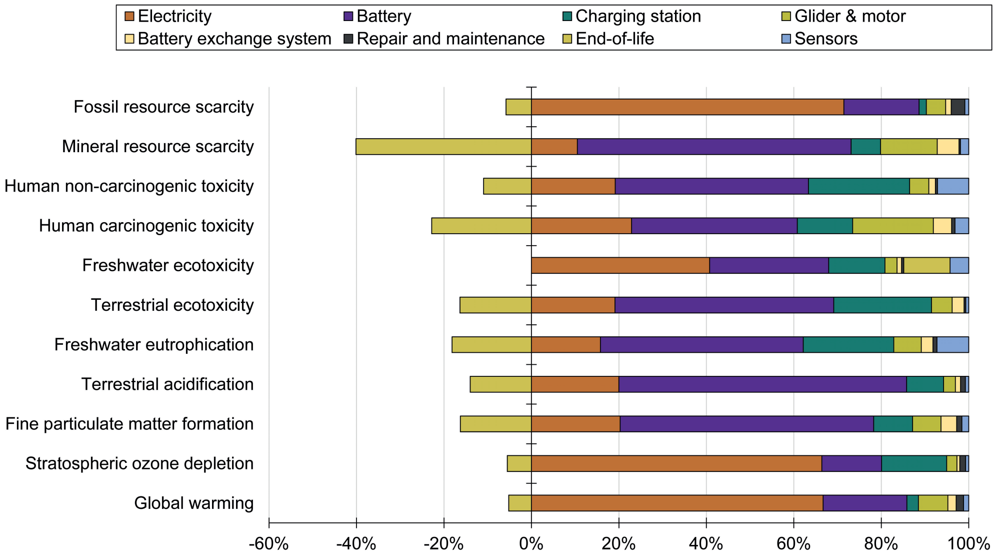

Figure 6. Cradle-to-grave (CTG) impact distribution using midpoint indicators for the battery electric vehicle (BEV) tractor system, including vehicle and infrastructure manufacturing, use phase and disposal. The most commonly used impact categories are shown. "Glider & motor" includes frame, chassis, tyres and wheels, other components, electric motor and glider assembly.

3.1.3. Damage Assessment

The damage assessment results, calculated as per ReCiPe 2016 [60,61], can be seen in Figure 7. The two major contributors to all three categories (human health, ecosystems and resource scarcity) were electricity use as fuel and the battery, which together contributed 75–89% of the impact. The battery was more significant for human health impact (44%), while electricity was the greatest contributing factor to impacts on ecosystems (68%) and resource scarcity (74%). In total, the BEV system resulted in an impact of 3.11×10^{-4} DALY ha^{-1} y^{-1} on human health, 9.09×10^{-7} species ha^{-1} y^{-1} on ecosystems and 13.4 USD$_{2013}$ ha^{-1} y^{-1} on resource scarcity.

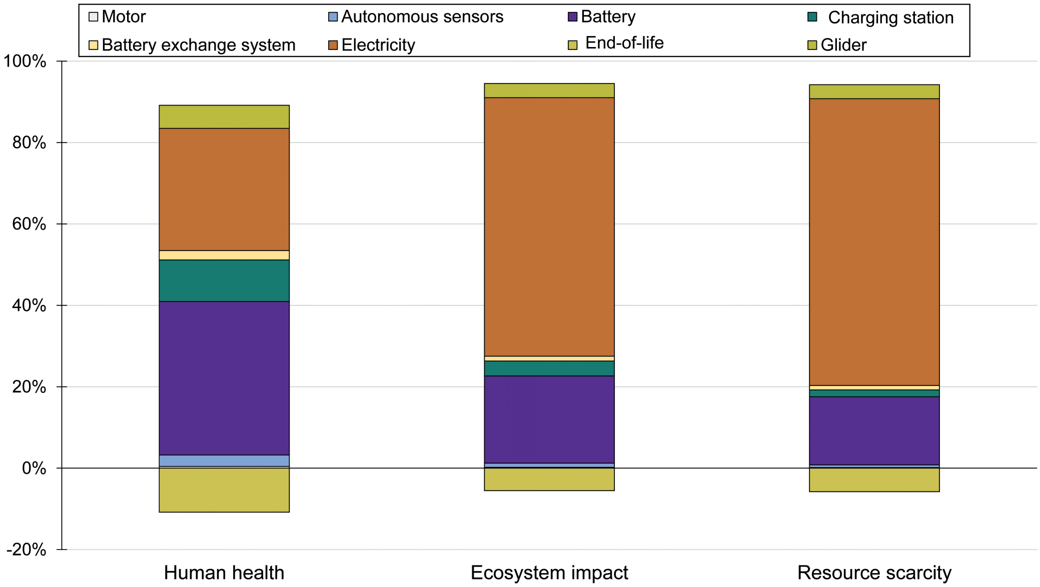

Figure 7. Damage assessment distribution for the battery electric vehicle (BEV) tractor system, showing impacts from manufacturing to disposal for each component category.

3.2. Comparative Results

Comparisons between the BEV and ICE systems for the midpoint impact factors are shown in Figure 8. The BEV tractor system had a larger impact than the ICE system in all categories in the GTG analysis. This was mainly due to batteries comprising a large proportion of the weight of the BEV. When comparing the CTG results, the BEV system showed lower impact than the ICE system in all impact categories apart from mineral resource scarcity, human carcinogenic toxicity and both kinds of ecotoxicity. The climate impact from the BEV system (102 kg CO_2eq.ha^{-1} y^{-1}) was 35% of that from the ICE system (293 kg CO_2eq.ha^{-1} y^{-1}).

On weighing and summarising the endpoint impact factors (Figure 9), it was found that the BEV system had an overall lower impact than the ICE system in all damage assessment categories: human health (−74%), ecosystem impact (−47%) and resource scarcity (−67%). For the single score, the BEV system had 72% lower impact than the ICE system. The results also showed that the use phase was most impactful for all categories apart from human health, where battery manufacturing had a higher impact than the use phase for the BEV system (Figure 9).

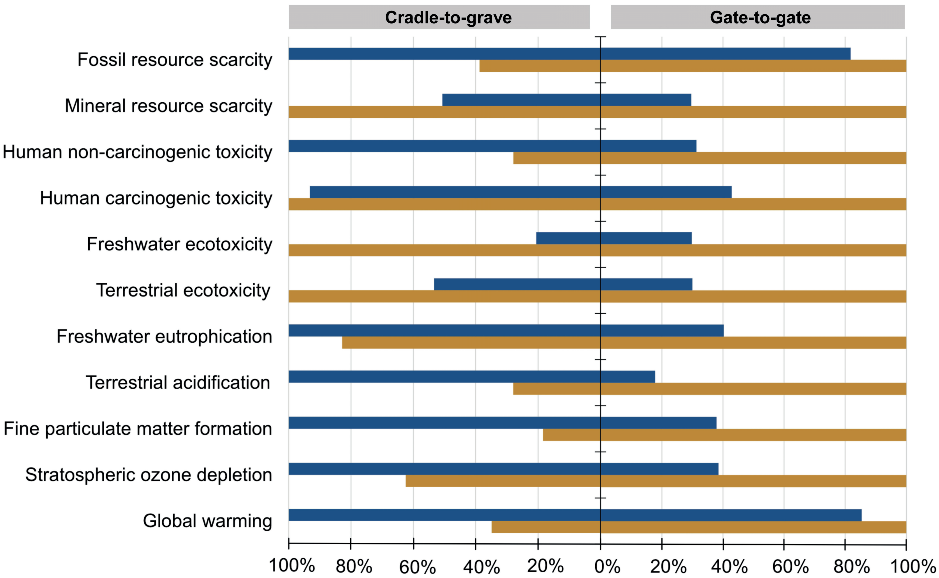

Figure 8. Midpoint impact comparison of the battery electric vehicle (BEV) system (orange) and the internal combustion engine (ICE) system (dark purple) in gate-to-gate (left) and cradle-to-grave (right) analyses of commonly used impact categories. Values are given as fractions of the largest values, instead of absolute values.

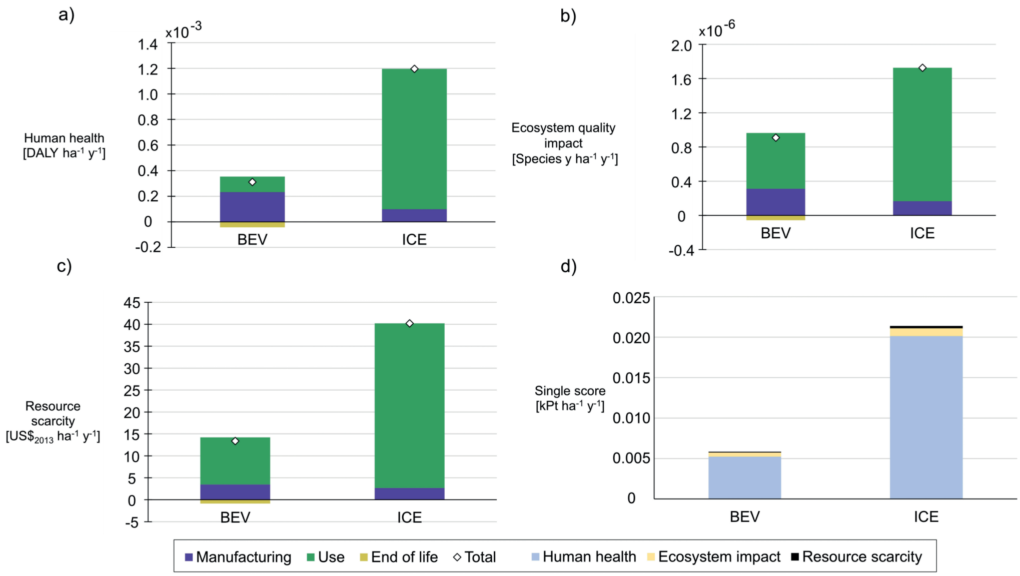

Figure 9. Comparative results for the battery electric vehicle (BEV) system and internal combustion engine (ICE) system in the damage assessment categories (**a**) human health, (**b**) ecosystem impact and (**c**) resource scarcity, as well as (**d**) Single score in the Hierarchist perspective according to the guidelines and values in [60].

3.3. Sensitivity and Uncertainty Analysis

A sensitivity analysis with one-at-a-time parameter change was performed. Absolute change, absolute sensitivity and relative sensitivity were calculated for changes in key parameters and are presented for both GWP and the weighted single score (Table 4). The equations used were as follows:

$$\text{Absolute change}: \ \Delta_V = P(V_\Delta) - P(V_0) \tag{2}$$

$$\text{Absolute sensitivity } S_A = \frac{P(V_\Delta) - P(V_0)}{P(V_0)} = \frac{\Delta_V}{P(V_0)} \tag{3}$$

$$\text{Relative sensitivity } S_R = \frac{S_A}{\Delta_P} \tag{4}$$

where Δ_V is the absolute change, $P(V_0)$ is the base value, $P(V_\Delta)$ is the resulting value after the parameter change (all three in the given impact unit), S_A is the absolute sensitivity (fraction), S_R is the relative sensitivity ($\%^{-1}$) and Δ_P is the change in the parameter (fraction).

Table 4. Results of sensitivity analysis for key parameters in the model for global warming potential (GWP) and single score values (italic), along with absolute change, absolute sensitivity and relative sensitivity.

	Base Case $P(V_0)$	**Absolute Change Δ_V**		**Absolute Sensitivity S_A**		**Relative Sensitivity S_R**	
Parameter Change	0%	−25%	+25%	−25%	+25%	−25%	+25%
GWP (kg CO_2eq.ha^{-1}y^{-1})							
Battery size	102.4	−5.2	5.2	−5%	+5%	0.20	0.20
Battery lifetime	102.4	2.6	−2.6	+3%	−3%	−0.10	−0.10
Vehicle lifetime	102.4	10.1	−4.0	+10%	−4%	−0.40	−0.16
BEV Energy use	102.4	−18.0	18.0	−18%	+18%	0.70	0.70
Motor size	102.4	−0.1	0.1	0%	0%	0.00	0.00
Glider material	102.4	−1.1	1.1	−1%	+1%	0.04	0.04
Single score (kPt ha^{-1}y^{-1})							
Battery size	5.84×10^{-3}	-3.99×10^{-5}	3.99×10^{-5}	−1%	+1%	0.03	0.03
Battery lifetime	5.84×10^{-3}	2.91×10^{-4}	-2.76×10^{-4}	+5%	−5%	−0.20	−0.19
Vehicle lifetime	5.84×10^{-3}	1.14×10^{-3}	-5.04×10^{-4}	+19%	−9%	−0.78	−0.34
BEV Energy use	5.84×10^{-3}	-6.04×10^{-4}	6.04×10^{-4}	−10%	+10%	0.41	0.41
Motor size	5.84×10^{-3}	-7.45×10^{-6}	7.45×10^{-6}	0%	0%	0.01	0.01
Glider material	5.84×10^{-3}	-4.89×10^{-5}	5.77×10^{-5}	−1%	+1%	0.03	0.03

Scenario Analysis

To evaluate different scenarios and changes in the assumptions made, key parameters in the model were varied. Only the results for climate impact are shown because it is the most prominently used category in the literature.

Because the Swedish electricity mix is not a good representation of electricity as a fuel in general, the electricity mix was varied. The Swedish mix has a high fraction of renewables and nuclear power, which the global or European mix does not. However, the Swedish margin used as default in this study is more akin to the general European electricity mix. It was found that the ICE system at 293 kg CO_2eq.ha^{-1} y^{-1} had a higher climate impact than all scenarios except electricity produced from hard coal. The Swedish and European margin electricity mixes had 65% and 60% lower GWP, respectively, with values of 102 and 116 kg CO_2eq.ha^{-1} y^{-1}, respectively. Electricity from hydropower and photovoltaics showed 83% and 77% reductions compared to the ICE case. The Swedish average mix, as described in Itten, Frischknecht and Stucki [40], was also included for comparison, with a total value of 45 kg CO_2eq.ha^{-1} y^{-1}.

Cases involving renewable fuel for the ICE were also considered because that is most likely the first measure taken to reduce GWP impact. Regular retail diesel in Sweden has a desired blend of 17.5% HVO (hydrated vegetable oil) [62], which was included, as was pure HVO. The GWP of HVO varies significantly depending on allocation method and feedstock used [63,64], so the possible range (7–78 g CO_2eq. MJ^{-1}) is shown in Figure 10, as well as that of Swedish HVO from 2016 [63,64]. The results showed that the low admixture diesel had a smaller impact than the case using global electricity mix, while the Swedish HVO case had a lower impact than Swedish and European margin electricity. However, it was still outcompeted by Swedish average mix and electricity from renewable sources.

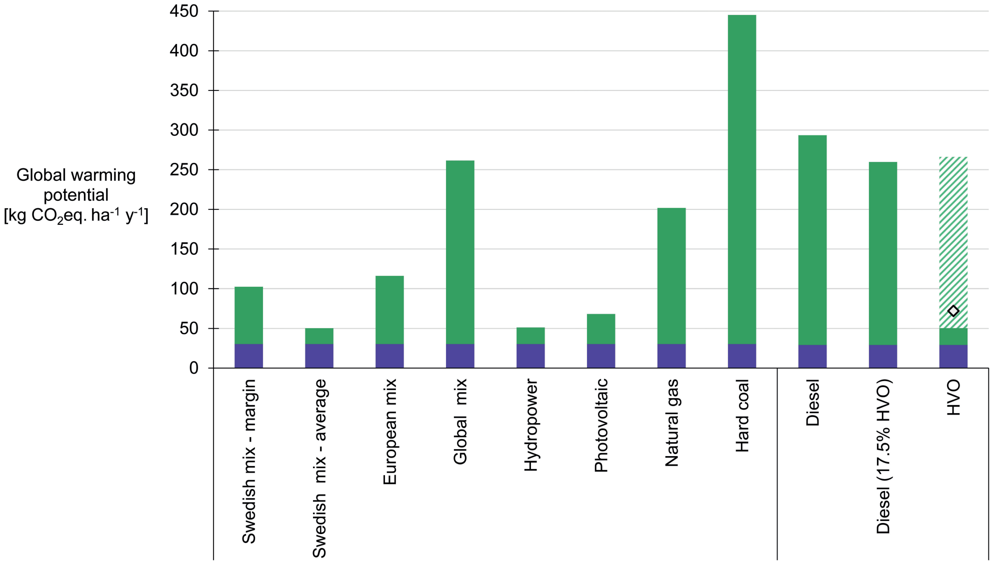

Figure 10. Scenario analysis of climate impact for different fuel sources for the battery electric vehicle (BEV) and internal combustion engine (ICE) systems, with the vehicle (purple) and fuel (green) presented separately. Disposal and end-of-life were included in the vehicle part, as was repair and maintenance. Swedish margin mix was used as the default in the modelling. The Swedish standard for drop-in blend of HVO in diesel is 17.5% [62]. HVO shown as the range presented in [63] (green diagonals) and with the value of Swedish-produced HVO from [64] (white diamond).

In addition, to account for uncertainty and give a baseline for the environmental potential of the end-of-life phase, a worst case scenario was explored with a different waste management for the BEV case. The reused fraction was instead assumed to be sent to landfill, resulting in a waste scenario with 84% of the material by weight ending up in landfill and 14% being incinerated for energy recovery. The resulting impact in GWP was a change in absolute sensitivity of +12%, and a single score increase of +20%. However, even with both these increases, the BEV system still had lower impacts than the ICE system in the stated categories.

4. Discussion

4.1. Assumptions and Scope

In this analysis, a consequential LCA with system expansion, instead of allocation and marginal energy sources, was used. Consequential LCA tends to lead to higher impacts compared to allocation assessments [29], which could explain why many values obtained in the calculations were higher than the literature values used for verification. However, due to the emerging state of the technology and the experimental nature of the current models, choice of the consequential LCA method can be considered reasonable because it describes a change in the life cycle [29,65].

The functional unit used was set to one hectare for mixed cereal (winter wheat, spring wheat, barley and oats) on a farm in the Uppland region of central Sweden. This functional unit can be considered too specific, but it builds on two previous studies by our research group using the same model, simulations and data [17,18] and allows for precise resolution. The results presented can be used as a general guideline for BEV tractors and show general dynamics that can also be seen in other analyses of battery electric work machines.

4.2. Inventory Model

The model used in this study was mainly based on secondary sources and little to no first-hand information. The early market state of the autonomous BEV tractor technology makes it difficult to find data, and there is no consensus on the best application of this kind of system because machines ranging in size from contemporary tractors to small drones are used. There are also different approaches to charging stations, suitable work and level of autonomy. Therefore, the system described and analysed here should only be regarded as a general exploration of one type of vehicle system, with all the assumptions and simplifications that entails. However, high resolution was sought for the most impactful inventory data points, such as battery production, battery recycling, diesel and electricity.

4.3. Model Outcome and Impact Assessment

The results of the inventory model in SimaPro showed that the BEV system had several parts with large impacts, but in the manufacturing stage, the battery caused the majority of the impact. This was partly due to the chemistry chosen, as several sources [6,7] state that NCA has a higher climate impact in general than other chemistries. It was also partly due to a BEV system with a requirement for several batteries being chosen. The battery exchange system modelled needs more batteries due to the simple dynamic of how the system works, where a depleted battery is quickly replaced with a fully charged one, thus requiring spare batteries. However, 4000 kg of battery is a large amount for a system of this size, even when divided between two vehicles, as each vehicle weighs ~2600 kg without battery. Vehicle systems with a different optimisation solution or system topography can be expected to have different impacts.

On comparing the two systems, it was found that the ICE system generally had a lower impact in the manufacturing stage (GTG), where both the battery production and the additional infrastructure provided a significant impact, on top of the vehicle manufacturing. However, the climate impact of the ICE system was 85% of the impact of the BEV system, so the difference was relatively minor, especially considering that 4000 kg of batteries were produced in the latter system. In all other impact categories apart from fossil resource scarcity, however, the ICE only had 40% or less of the impact of the BEV system, showing the importance of studying several impact categories.

On studying the entire life cycle, it was found that the BEV system had lower impacts than the ICE system in all categories apart from mineral resource scarcity, human carcinogenic toxicity, and terrestrial and freshwater ecotoxicity. The BEV system gave especially high reductions in global warming, fine particles and acidification, mostly due to the higher energy efficiency of the BEV driveline and the lower impact of electricity as a fuel compared with diesel. These factors combined meant that the use phase heavily favoured the BEV system because, even though electricity was still a significant part of the system impact, it had a lower impact than diesel. In addition, some of the high-impact materials from the manufacturing phase could be recycled and reused, further lowering the overall impact. In the damage assessment, the BEV system had lower impacts than the ICE system for human health (−74%), ecosystem impact (−47%) and resource scarcity

(−67%). For the single score, BEV had 72% lower impact than the ICE system. It is also worth noting that the data on diesel emissions were from 2007, and since then advances have been made in combustion engines in tractors.

It was found that the manufacturing of batteries and the electricity used as fuel constituted the majority of the impacts, both in the midpoint and endpoint analysis. This suggests that the type and size of battery are very impactful, as is the electricity used. Several sources agree that the impact of batteries is highly relevant in BEV systems, and they present similar findings to those in this study [10,50,56]. The results on the impact of the origin of electricity used are in line with the findings in Nordelöf, Messagie, Tillman, Söderman and Mierlo [10] and Marmiroli, Messagie, Dotelli and Mierlo [55].

4.4. Comparison to Other Studies

As the battery was the most impactful part of the manufacturing process for the BEV system, it was important to check that the values used were in line with those reported in the literature. Verification against literature values on global warming potential (Figure 11) showed that the value obtained for the modelled NCA battery module (155 kg CO_2eq kWh^{-1}) was slightly higher than the literature values for NCA batteries (range 120–133 kg CO_2eq kWh^{-1}) [34,49,66]. It was also in line with or slightly higher than the general values for nondescribed chemistries in the literature (range 61–175 kg CO_2eq kWh^{-1}) [6–8,67]. However, some studies report significantly higher impacts, especially Emilsson and Dahllöf [6]. This led to the conclusion that the simulated value was slightly high, but still realistic.

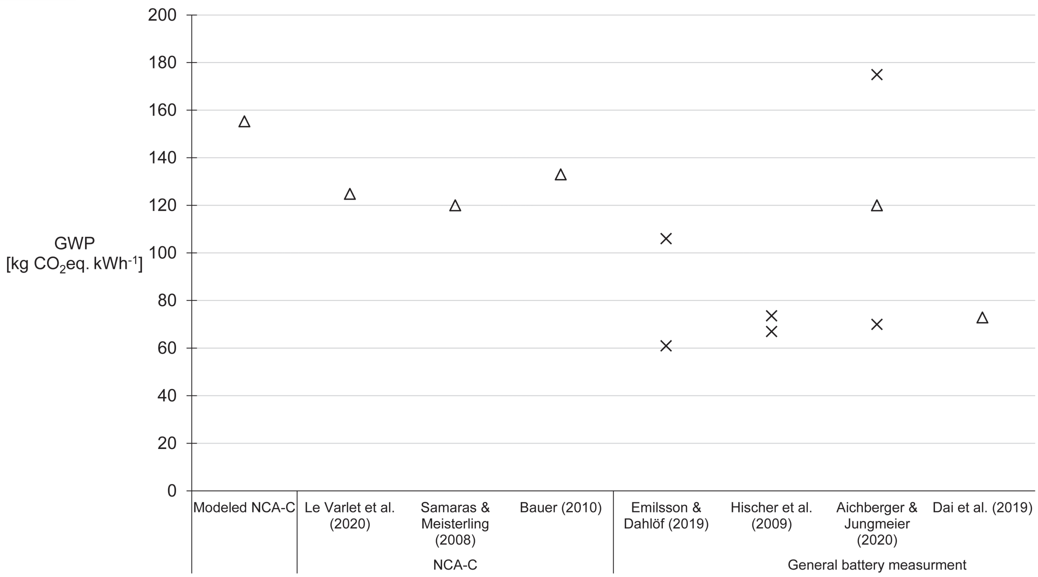

Figure 11. Comparison of global warming potential (GWP) impact for the modelled nickel cobalt aluminium-graphite electrode (NCA-C) battery and the literature values. When given, the average value is represented by Δ, and high and low values by ×.

The values used for the ICE system were found to be slightly higher than the literature values. The value calculated for the modelled system was 293 kg CO_2eq.ha^{-1} y^{-1} for the entire life cycle (implement, fertiliser and field emissions excluded). Similar studies have reported values of 140 kg CO_2eq.ha^{-1} y^{-1} [59] and 160 kg CO_2eq.ha^{-1} y^{-1} [20] for machinery operations. However, the entire set of field operations was not studied in those cases, and the energy use was lower. In addition, as discussed by Lagnelöv, Larsson, Nilsson, Larsolle and Hansson [17], the energy use of the studied simulated system was slightly higher than corresponding studies in the literature, which most likely carried over for both the ICE and BEV systems. This difference could be explained by the inclusion of more operations, higher data resolution or more energy-demanding soil types (high clay fraction).

The electricity mix used was of high importance. The Swedish margin electricity mix gave a total CTG GWP impact of 102 kg CO_2eq.ha^{-1} y^{-1}, while that for the Swedish average electricity mix was 45 kg CO_2eq.ha^{-1} y^{-1}, i.e., roughly half the total impact. The marginal mix was based on 41% natural gas, 35% wind power and 24% biomass [40], while the average mix consisted of 41% hydro power, 40% nuclear power, 7% wind power, 2.5% biomass and the remainder imported [40]. These values are for 2014 but were verified and found to be reasonably close to the values for 2018 [41,42]. It can be discussed whether one or another of these mixes is the more methodically correct choice of electricity, but such discussion fell outside the scope of this study. The scenario analysis in Section 3.3 gave an overview, instead of a deeper analysis.

4.5. Sensitivity Analysis

Sensitivity analysis based on the resulting response in GWP and single score for parameter changes showed that the energy use of the BEV system had the highest absolute and relative sensitivity for both GWP and single score, as an increase of 25% in the parameter led to an increase of 18% and 10%, respectively. It was followed by the vehicle lifetime, indicating that the assumptions made for these parameters had a high impact. The lifetime of the battery was varied separately and found to have a lower impact for both GWP and single score than the total vehicle lifetime. Glider material use and the size of the motor had very low importance in both categories, as had the battery size for the single score category. However, battery size was impactful for GWP. By ensuring the lowest possible energy use (or the use of cleanest possible energy) and a long lifetime over which to attribute the manufacturing impact, a low impact is more likely.

Exploration of different end-of-life treatments for the BEV showed an increase in GWP (+12%) and single score (+20%). This indicates that waste management is an important part of the environmental impact for these kind of systems and that care should be taken in relevant assumptions made when modelling. In LCAs, recycling is often assumed to be done better or more frequently than the empirical data indicate, and general knowledge of that part of the process is low [6,10,27]. Because a large part of the impact of the BEV system was in the production stage, recycling and waste management are important because they represent ways to mitigate the impact of the manufacturing phase and to reduce the need for virgin material.

Replacing diesel with HVO was shown to be a way to reduce impact for the ICE system, but it was heavily dependent on the feedstock and process used. The literature values vary from 7 to 78 g CO_2eq. MJ^{-1}, and hence they suffer from inherent uncertainty in the data, as shown in the review by [2], but also confirm that the interval used here was reasonable. In addition, using HVO would still suffer from reduced driveline efficiency compared to the electric driveline and result in higher overall energy use. However, use of biofuels can be an important initial step to reduce the impact of machinery without replacing the current tractor fleet, a process that is itself likely to have a substantial environmental impact.

Because the use phase was impactful for both the BEV and ICE cases, the fuel used is of great importance. The difference between the best case for electricity (hydropower) and the worst case (hard coal) was close to a nine-fold increase in climate impact. Of all the electricity sources assessed, hard coal was also the only one with a worse climate impact than the ICE system. Electricity origin was also important for the overall results, as there was a large difference in the total GWP of the system when using Swedish (102 kg CO_2eq.ha^{-1} y^{-1}), European (116 kg CO_2eq.ha^{-1} y^{-1}) or global electricity mix (262 kg CO_2eq.ha^{-1} y^{-1}). Choosing Swedish marginal mix over Swedish average mix also doubled the total GWP impact. Based on these results, it seems that all other assumptions were eclipsed by the origin of the electricity in the use phase. This is also partly true for on-road BEVs, but the more intense use of work machinery and the higher yearly energy use in agriculture make the choice of electricity even more important for that class of vehicles. There are large reductions to be gained in changing to a BEV system, but choosing low-impact electricity is vital.

4.6. Implications and Future Research

The results indicate that changing from a diesel vehicle to a battery electric one in a work machinery setting has the potential to drastically decrease the environmental impact in general and GHG emissions in particular over the entire lifespan, even when a large number of batteries is required to be manufactured. While the manufacturing of the batteries was a large part of the impact for the BEV system, it was not detrimental to the overall result. This finding is important for both heavy on-road vehicles and mobile nonroad machinery. Tractors are used intensely during critical points in production (sowing, harvesting) but on a yearly basis work a low number of hours compared to other work machinery. With the tractor system showing a general reduction in environmental impact with a use phase—and therefore fuel use, limited to parts of the year—vehicles with higher yearly usage have a higher potential reduction in environmental impact in the use phase. The outcomes of this study can serve as a precursory positive example of the benefits of transitioning work machinery from diesel to electricity as fuel, and they mark electricity origins and battery manufacturing as important hotspots for further consideration.

The majority of the LCAs performed on BEVs have been focused on GWP as the dominant, or only, impact category. The results impact assessment from this study showed that the different systems, and the different system parts, had different impacts. The BEV systems had a drastic reduction in fine particulate matters compared to the conventional system in the CTG-perspective, but they showed an increase in ecotoxicity. In order to obtain a full picture of the systems impact on the environment both locally and globally, an expanded assessment of several categories and damage categories is beneficial in order to gain important information. The usage of multiple impact categories when performing LCAs has been stated previously [27,60] but remains a recommendation to the industry, policymakers and researchers.

Future research is recommended on the practical applications of vehicle systems similar to the one studied in this article. Verification of simulation data with field trials is an important part in determining the long-term sustainability of the technology. Additional research is also recommended on the secondary effects of using lighter, self-driving tractors, such as soil compaction, marginal field use and increased field trafficability.

5. Conclusions

The LCI and LCIA of an autonomous battery electric tractor system were simulated and calculated, considering a total of eleven midpoint impact categories, three endpoint impact categories and an aggregated single score. The results showed a climate impact of 34 kg CO_2eq.ha^{-1} y^{-1} for GTG and 102 kg CO_2eq.ha^{-1} y^{-1} for the entire life cycle (CTG). This was only 35% of the CTG GHG emissions of the diesel tractor system studied (293 kg CO_2eq.ha^{-1} y^{-1}), indicating that there is a high potential for a reduction of lifecycle GHG emissions by using battery electric tractors.

Battery manufacturing and the electricity used for fuel represented important hotspots for all types of impact categories. The BEV system showed a higher impact than the ICE system across all categories in the manufacturing phase, with battery materials and assembly in particular having a large impact.

In a CTG perspective, the BEV system had substantially lower impacts compared to the ICE system in several impact categories, most notably climate change, eutrophication, acidification, fine particulate matter and fossil resource scarcity. The BEV system had a higher impact in categories dealing with mineral resource scarcity, carcinogenic toxicity and freshwater and terrestrial ecotoxicity. A long lifetime, energy-intense use phase and a high recycling rate favours the BEV system.

For both the ICE and BEV systems, the use phase was the most impactful, and the fuel used was highly relevant. For the BEV case, the choice of electricity mix used for recharging resulted in a total GWP impact ranging from 45 (hydropower) to 445 (hard coal) kg $CO_2eq.ha^{-1}\ y^{-1}$, i.e., an approximately 10-fold difference. Although all but one of the electricity mixes had a lower impact than the diesel system, low climate impact was highly dependent on low-impact electricity. The choice of electricity was by far the most decisive factor for climate impact, eclipsing all other factors considered, as confirmed by sensitivity analysis.

In CTG endpoint analysis, the BEV system was found to have a notably lower impact than the ICE system in the categories human health (−74%), ecosystem impact (−47%) and resource scarcity (−67%). In the summarised and weighed single score category, the BEV system showed a 72% reduction in impact compared with the conventional ICE system. This result corroborates the hypothesis that changing from a diesel based to an electricity-based system, as described in this study, leads to lower total environmental impacts.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su132011285/s1. S1—Inventory lists [Spreadsheet]; S2—LCI and LCIA results [Spreadsheet]; S3—Chosen impact categories (Table S3a), ReCiPe equivalent impact categories in midpoint and endpoint (Table S3b) and conversion factors for the Hierarchist perspective (Table S3c) [Spreadsheet]

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Impact of lowered vehicle weight of electric autonomous tractors in a systems perspective

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ABSTRACT

Modern agriculture rely on heavy machinery that has increased risk of detrimental soil compaction of arable fields. This can lead to negative effects such as reduced yields, reduced field trafficability and increased fuel use. Electric, autonomous tractors makes it possible to replace one heavy machine with several lighter without increased labour costs. In this study, the economic and environmental effects of reduced soil compaction for smaller autonomous tractors were assessed and compared to a scenario with conventional tractors. A discrete event simulation of a Swedish 200 ha grain farm with clay soil was used for the calculations. The electric, autonomous system had lower soil compaction impacts as well as other benefits, and reduced cost in total from 385 to 258 € ha-1 and the climate impact from 270 to 77 kg CO_2eq ha^{-1} compared to the conventional scenario. Soil compaction constituted 20% of the cost and 26% of the climate impact for the conventional scenario. It was concluded that soil compaction was impactful in machinery studies, especially on heavier soil like clay, and should not be omitted. Soil compaction avoidance alone was not impactful enough to warrant a change to electric, autonomous tractors but it reinforced already existing trends and further improved the cost and environmental benefits.

1. Introduction

Sustainable agriculture is required to maintain a stable food supply for a global growing population that is currently being met by intensification of food production. Since 1961, caloric supply per capita has increased by one-third globally, with the use of inorganic fertiliser increasing nine-fold [1]. This increase in food supply has been accomplished through increased machine capacity, with the weight of tractors used in agricultural field operations increasing over time, resulting in static wheel loads increasing from 1000 kg to 4000 kg in the period 1955-2000 [2]. In addition, agriculture is both a contributor to climate change and one of the sectors most affected by it. A study by Lobell et al. [3] indicated a 5.5% reduction in wheat production globally between 1980 and 2008 compared with a case without climate effects. Shukla et al. [1] pointed out several detrimental future effects of climate change on agriculture, such as desertification, increased frequency of extreme weather events, soil degradation and yield reductions, leading to a decisive and lasting negative effect on global food security. Agricultural production contributed 11.2% of total global greenhouse gas emissions in 2010 [4], with around 1% of all global emissions deriving from agricultural machinery use [5], which is almost entirely dependent on fossil fuels.

A proposed solution for reducing machinery-related emissions, including those from heavy non-road machinery, is electrification of drivelines [6]. There are several political goals that target electrification as a key technology, such as a fossil-free vehicle fleet in Sweden by 2030 [7] and a carbon-neutral European Union (EU) by 2050 [8]. Previous studies have reported potential for electric agricultural machinery to be cost-competitive [9,10] and environmentally beneficial [11,12] compared with conventional vehicle systems. In order to maintain economic viability and reduce drawbacks with electric drive, vehicle autonomy has been proposed as a synergetic technology solution and key driver [6]. Autonomy maximises the time in which the vehicle can work in the field, while reducing the detriment of longer charging periods by reducing operator costs and allowing for more work hours per day. As an indirect effect, it is possible to work with multiple lighter vehicles instead of a single larger machine, with equal or improved performance. In addition to influencing the cost and environmental impacts, switching to self-driving and electric vehicles can lead to lighter vehicles, which might have a beneficial effect on soil health due to the

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reduced load, as there is a link between vehicle weight and soil compaction.

Soil compaction involves a reduction in soil volume, specifically in the air-filled fraction, and an associated increase in bulk density [13,14]. Causes of unwanted soil compaction include increasing machine weight, intensive cropping, short crop rotations, overuse of machinery and inadequate soil management [15]. The rate of soil compaction is increasing globally [16] and problems have been reported worldwide [15]. Soil compaction has several separate or interconnected effects on agriculture, such as decreased water conductivity [17], decreased plant growth, reduced fertiliser efficiency, lower crop yield and increased machine use due to increased soil density [18], all of which can be detrimental to agricultural production and the environment. Long-term cereal yield losses from soil compaction are estimated to be 4-20% [2,16, 18,19]. According to Graves et al. [18], soil compaction imposes an annual cost to agricultural production in England and Wales of 200 M€ y^{-1}, or 56-140 € ha^{-1}. In the same study, the mean annual cost of soil erosion in Europe was estimated to be 122 € ha^{-1}. Keller, et al. [2] and Hamza and Anderson [15] reported that roughly one-third of arable land in Europe (33 Mha) was negatively affected by soil compaction in 1991, and the proportion has likely increased since then, with Keller and Or [20] suggesting that 20% of the global arable land is at risk of chronic subsoil compaction. Chamen et al. [19] estimated that mitigating soil compaction could increase gross margin by 22 £ ha^{-1} and avoiding soil compaction could increase gross margin by up to 118 £ ha^{-1} for clay soils. Previous life-cycle assessment (LCA) studies of soil compaction concur that it has a significant environmental impact, mainly related to reduced yield levels [21,22] and increased nitrous oxide (N_2O) emissions due to poor soil aeration [19].

Some previous studies [19,23,24] have proposed use of lighter machines as a soil compaction avoidance strategy, but have pointed out that autonomous operation will be needed to make lighter vehicles economically interesting to farmers. Other studies have also suggested that electric field tractors require autonomy to compete economically with contemporary conventional tractors, which also allows them to be lighter [10,25]. This indicates the possibility of a synergetic solution where vehicle autonomy addresses both concerns. When modelling the effects of soil compaction, previous works have focused separately on the physical system [26], economic cost [2,18] or environmental effects [21]. Soil compaction is often not considered in machine analysis, but its inclusion has been recommended [10].

By studying in parallel all direct and indirect effects of a system change on the performance, economics and environmental impact of an agricultural machine system, a greater understanding can be reached and more informed recommendations can be made. The aim of this study was to extend previous work studying the change from diesel tractors to self-driving electric tractor systems by including soil compaction effects and assessing the general economic and environmental impacts. This was done through simulations of vehicle systems in Swedish agriculture. The hypothesis tested was that use of lighter machines, made economically competitive by self-driving technology, can reduce soil compaction, with beneficial economic and environmental effects.

2. Material and methods

The analysis comprised dynamic discrete-event simulation of a 200-ha farm in Uppland, Sweden, growing four different kinds of cereal (winter wheat, spring wheat, barley and oats). Soils in the Uppland region have a high clay content, typically 40-60% [27]. The simulation included tractor parameters, soil data, weather effects and output time requirements, delays, energy use and machine logistics. Soil compaction effects were also included in the model and the resulting output was quantified (Fig. 1).

The results from the model were used to calculate total annual cost of operation, using a method described by Wu, et al. [28] and Lampridi et al. [10], together with straight-line depreciation and average interest rate methods, combined with an economic model previously used in Lagnelöv et al. [9]. The results were also analysed in an environmental LCA study using the ISO methodology [29], characterisation factors from the ReCiPe method [30,31] and inventory presented in [11]. In addition, only changes directly related to a change in tractors were included, so the harvest, inputs, seeds and implements were omitted due to the assumption of having the same cost and environmental impact in all cases.

The focus in the analysis was on long-term subsoil compaction, rather than shorter-term topsoil compaction. Any change in machine systems would mainly affect the subsoil over a certain time horizon and the scope of this study was therefore that time horizon. According to Hamza and Anderson [15], topsoil compaction is caused mainly by ground pressure and can therefore be lessened by increasing the tyre-soil contact area, while subsoil compaction is related to the axle load and can be lessened by decreasing vehicle weight.

A difficulty when modelling soil compaction is that most arable land in modern agriculture is already compacted to some degree [2,18], so data on yield levels and vehicle energy use already implicitly include losses from soil compaction, preventing comparison to a vehicle system with no soil compaction effects. Keller et al. [2] argue that most field trials compare normally compacted soils (arable land trafficked in a normal manner) with experimentally compacted soils, since most agriculturally managed soils are at least partly compacted. Therefore yield penalties identified in the literature derive from further compaction of already compacted soil and not compaction of uncompacted soil (also known as virgin soil or not trafficked soil) [2]. For ease of presentation

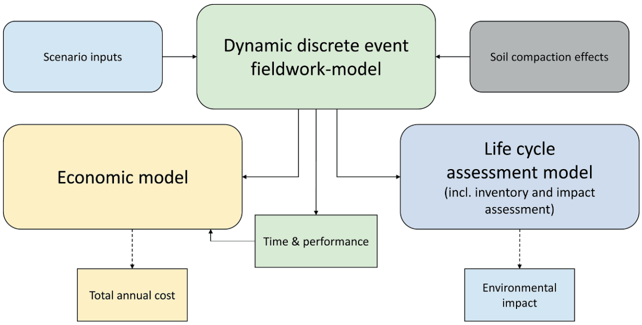

Fig. 1. Overview of models (oblongs), their interconnections (arrows) and inputs/outputs (rectangles).

and for comparison with literature data, this study made the same assumption, using normally compacted soil as the baseline and allocating the negative effects of further soil compaction to scenarios with heavily compacted soil due to high vehicle weight.

2.1. Model input and scenarios

Model input to the different scenarios compared, encompassing different technology pathways, is shown in Table 1. To assess the impact of soil compaction, heavy and light vehicles were considered and electric and diesel tractors, which were either manned or autonomous.

The simulation considered a conventional cropping system for grains, including cultivation, harrowing, roller packing, sowing, fertilisation, spraying and ploughing. The tillage depth was 10 cm, except for ploughing where it was 20 cm [32]. A soil with a high (>40%) clay fraction was assumed. The tractors were simulated to only work when the soil moisture content was under the limit for workability from de Toro and Hansson [33], which was assumed to be 85% of field capacity for general tillage and 110% of field capacity for ploughing, using field capacity from Witney [34].

Two scenarios with a single diesel-powered 250-kW tractor weighing 10,800 kg were included as the current state of technology, to which all other scenarios were compared. In one of those scenarios, the tractor was assumed to have an autonomous system, but it was otherwise identical to the other conventional tractor scenario. A scenario with a large electric tractor was included to analyse the difference between one larger machine and several smaller machines. The main alternative scenario assumed two 50-kW electric autonomous tractors, each weighing 4047 kg, of which 1000 kg was batteries, as in Lagnelöv et al. [11]. This solution has been shown previously to be competitive in several metrics [9,11,25]. For comparative purposes, a similar scenario with two 50-kW autonomous tractors with diesel as fuel was also included. A final scenario where three electric machines were used was included to assess a scenario with high operational capacity and rate of work.

Energy use in the electric scenarios was based on fieldwork force equations from [35], adjusted down by 15% to fit field test results since the original equations have been reported to overestimate energy use [36,37]. The diesel scenarios used data from field tests performed in the Uppland region [38], leading to diesel energy consumption for 200 ha of mixed cereal cropping of 108,803 kWh y^{-1} (or 54 L ha^{-1} y^{-1}) for normally compacted soil and 151,978 kWh y^{-1} (76 L ha^{-1} y^{-1}) for heavily compacted soil. The diesel energy consumption for heavily compacted soil was calculated using the increase in fuel use presented in Section 2.2.3.

2.2. Soil compaction and vehicle weight

Tractors with high weight have been found to cause elastic deformation in soil, with the effect persisting in layers deeper than 40 cm after the pass if total vehicle weight exceeds 8000 kg [15,39]. It has been shown that tractors with weight below 5300 kg only compact the top 40 cm of soil [39,40]. Compaction in the topsoil (0-25 cm) can be seen as reversible within one or a few years, while the mid soil level (25-40 cm) remains compacted for up to 10 years and compaction occurring below 40 cm is considered to be very long-lasting or permanent [21,22,41] (Fig. 2).

In the comparison in this study between heavier (10,800 kg) and lighter (3-400 kg) vehicles, it was assumed that the tractors with lower weight compacted the soil in a reversible way, while the heavier machines led to long-lasting or irreversible soil compaction (in practice, the effect of vehicle weight on soil compaction is more gradual). This is in agreement with recommendations from Horn and Fleige [42], who recommended an axel load of under 3300 kg to avoid long-term subsoil compaction. The focus in this study was mainly on long-term soil compaction effects resulting from making a lasting change in machinery systems, but the effects of temporary soil compaction are touched upon in the discussion.

Among the many adverse effects of soil compaction, three were considered in the present analysis: 1) reduced trafficability due to a reduction in soil hydraulic conductivity, 2) reduced crop yield due to rooting difficulties; and 3) increased fuel use due to increased soil density/resistance. These factors are directly related to vehicle systems and have been identified as impactful [2,15,23,44].

2.2.1. Reduced hydraulic conductivity

Soil compaction results in a reduction in soil hydraulic conductivity at saturation (K_{sat}), which leads to slower drying of the soil and subsequently a narrower window of trafficability [43]. Keller et al. [2] found that the hydraulic conductivity decreases linearly with increasing soil compaction and estimated that the average hydraulic conductivity of subsoils (0.25-0.7 m) is 40% lower for managed arable soils than unmanaged soils. In a field study by Keller et al. [17], a decrease of three

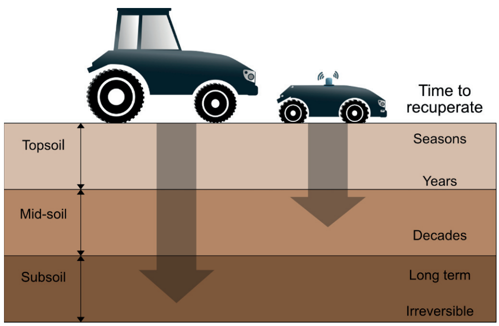

Fig. 2. Graphical overview of soil compaction at different depths and for different vehicle weights [21,23,43]. Soil compaction depth shown as grey arrows.

Table 1
Input to the model of key parameters in the different scenarios. Batteries and vehicle weights from Lagnelöv et al. [11], with assumed battery gravimetric energy content of 0.1 kWh kg^{-1}.

Scenario no.	Fuel	Number of vehicles (N_v)	Rated power (P_r, [kW])	Energy carried [kWh, (l)]	Extra battery packs	Working time [h d^{-1}]	Mass, incl. batteries [kg]
1	Diesel	1	250	4684 (463)	-	10[a]	10,800
2		1	250	4684 (463)	-	24[b]	10,800
3		2	50	1315 (130)	-	24[b]	3047
4	Electric (Battery Exchange	2	50	100	2	24[b]	4047
5	System)	3	50	100	2	24[b]	4047
6		1	250	200	2	24[b]	12,800

[a] Manned
[b] Autonomous.

orders of magnitude in K_{sat} was observed in the topsoil directly after a compaction event. After two weeks, a 74% reduction of K_{sat} remained. Assuming that this finding is indicative of changes in saturated hydraulic conductivity in general, this would lead to a reduction in K_{sat} from 21.3 mm d^{-1} to 5.5 mm d^{-1} using the soil parameters and soil moisture balance equation from Witney [34] as in Lagnelöv, et al. [25]. In our model, K_{sat} was mainly relevant for the drainage rate of the soil. For heavily compacted soil a hydraulic conductivity constant of 5.5 mm d^{-1} was used, while for normally compacted soil the base value for clay soils (21.3 mm d^{-1}) in Witney [34] was used. The heavier vehicles (10.8 tonnes) were assumed to give rise to semi-regular compaction events when following normal agricultural practise, as described by [2], and the value for compacted soils was applied. The lighter vehicles (3-4 tonnes) were assumed to only cause reversible levels of compaction already included in yield data from empirical sources.

2.2.2. Reduction in crop yield

The focus in this study was on long-term yield loss as an effect of choice of machinery system. A constant annual yield loss of 8%, as stated in Keller et al. [2] for Swedish soil with high clay content, was assumed for the heavy vehicles. No loss of yield was assumed for the vehicles with lower weight, as the soils were assumed to be normally compacted and normal yield data applied. Some studies suggest time-dynamic recovery of yield levels after compaction events [2,22,39], but this was beyond the scope of the present study. Yield losses were re-calculated to a direct economic cost, using the data in Table 2.

2.2.3. Increased fuel use due to higher soil density

Soil compaction leads to an increase in soil density, which necessitates either higher-powered (and heavier) machinery or more passes, both leading to an increase in fuel consumption compared with less compacted soil [21]. Graves et al. [18] assumed an 87% increase in use in fuel energy for all seedbed preparation operations on clay soil. In this study, it was assumed that harrowing, ploughing and cultivation were affected by soil compaction, while seed drilling, roller packing, and fertiliser and pesticide spreading were unaffected.

2.3. Economics

The economic calculations were based on the model for total cost of ownership described in Lagnelöv et al. [9], with the size of fuel tanks updated to reflect common practice (Table 1). The model was used to assess the total annual cost of owning and using fieldwork vehicle systems, including investment cost, maintenance and repair, capital costs, fuel use, operator cost and the economic effect of soil compaction. Several cost factors normally included in agricultural cost assessments were assumed to be similar for all scenarios and omitted from the detailed calculations. These included the farm itself, vehicle housing, insurance, inputs, implements and seeds. The cost of infrastructure for diesel refuelling was omitted, as such infrastructure was assumed to be already present on-site, but the installation cost of electric refuelling infrastructure (charging stations and battery exchange systems) was included, as very few farms have this infrastructure yet.

The autonomous vehicles were assumed to be capable of operating by themselves, but requiring oversight or some degree of handling for a fraction of the operating time, with this fraction varying for different tasks. This meant that even the autonomous vehicles had an operator cost that increased with increasing active time. It was assumed that 10% of charging, 20% of fieldwork and 30% of road transport needed oversight by an operator [9].

Table 2
Field and grain yield data used in the study. Yield is 3-year average for Uppsala, 2019–2021 [45–47], and grain prices are 5-year (2017-2021) aggregated means from selected wholesale buyers [48].

	Winter wheat	Spring wheat	Barley	Oats
Yield [kg grain ha^{-1}]	6809	4557	4847	4321
Wholesale price [SEK kg^{-1}]	1.65	1.76	1.57	1.36
Wholesale price [€ kg^{-1}]	0.152	0.163	0.145	0.125
Revenue [€ ha^{-1}]	1,036	741	702	542

The electricity price was calculated as a three-year average (2018-2020) for an industrial consumer with yearly consumption of 50-200 MWh and the total price, excluding VAT, was 0.076 € kWh^{-1} [49]. Diesel prices were taken from [50,51] and aggregated as a three-year average (2018-2020) to match the time period of the electricity prices, resulting in a pump price of 1.42 € L^{-1}. These prices were modified with the Swedish tax reduction for agriculture from energy and CO_2 taxes and VAT exemption (normally 25% on production costs and taxes). The tax reduction was 178 € m^{-3} (1930 SEK m^{-3}) at the start of 2022, but a new level of 363 € m^{-3} (3930 SEK m^{-3}) has been proposed from 2022 by the Swedish government [52] and was used in this study. It results in an effective diesel price for Swedish farmers of 0.77 € L^{-1}, or 0.076 € kWh^{-1} using conversion factors from Reif and Dietsche [53].

2.4. LCA

The environmental assessment took the form of consequential LCA, following the ISO 14040:2006 standard methodology [29]. The scope of the assessment was production and assembly, use and end-of-life (EoL) phases of the life cycle for the different vehicle scenarios considered. The focus was on the vehicle systems performing field operations. Inputs, seeds, implements and harvesting were omitted. The method presented in [11] was followed, with the same assumptions, sources and inventory. The ReCiPe method [30,31] was used for characterisations and weighting in life cycle impact assessment (LCIA), applying the hierarchist perspective as it is the default for the method and hence commonly used. Modelling and calculations were performed in the LCA software SimaPro (v.9.0.0.49, PRé sustainability, Amersfoort, The Netherlands). The inventory (Table 1) was made using the models from [11]. The infrastructure was assumed to be scaled proportionally, i.e. larger battery pack size required a larger battery exchange system.

The LCA results were calculated for the midpoint global warming potential (GWP) impact factor and for the aggregated damage categories human health, ecosystem impacts and resource scarcity. GWP is the most commonly presented metric for battery electric vehicles and the damage categories give a holistic picture of the environmental impact, using all 18 impact categories available in SimaPro. Supplementary material S.1 shows the results for the 18 midpoint and endpoint characterisation factors and the damage categories, and an aggregated single score for all vehicle system scenarios considered.

The LCA included vehicle, fuel and additional fuel use. The vehicle category included production, assembly, maintenance, repair and EoL for the vehicle, batteries and charging infrastructure. The assessment of fuels showed the impact originating from the use of diesel (with no blend-in biofuels) or electricity (Swedish marginal electricity) [54,55].

2.5. Sensitivity analysis

As the simulations and calculations required assumptions and aggregation of models with different levels of detail and certainty, a nominal range sensitivity analysis (also known as once-at-a-time sensitivity analysis) was performed for key parameters in vehicle performance, cost and environmental impact. Some alternative values or scenarios of certain interest were also explored and the resulting effects calculated. Since the models used are deterministic and the main objective of the sensitivity analysis was to find the most impactful parameter, the analysis method chosen to verify and validate the results is in line with recommendations [56,57]. As in Lagnelöv et al. [11], the analysis was performed for absolute change (change in the base unit), absolute sensitivity (change in percent) and relative sensitivity (change per percent) Eqs. (1)–((3)):

$$\Delta_V = P(V_\Delta) - P(V_0) \quad (1)$$

$$S_A = \frac{\Delta_V}{P(V_0)} = \frac{P(V_\Delta) - P(V_0)}{P(V_0)} \quad (2)$$

$$S_R = \frac{S_A}{\Delta_P} \quad (3)$$

where Δ_V is the absolute change, $P(V_\Delta)$ is the resulting value after the parameter change, $P(V_0)$ is the base value, S_A is the absolute sensitivity, S_R is the relative sensitivity ($\%^{-1}$) and Δ_P is the fractional change in the parameter. The results were presented as change in GWP and in total annual cost.

3. Results

The selected scenarios were simulated and analysed to determine the effects of different factors. The economic, environmental and performance results are presented, with the impacts of soil compaction being described specifically.

3.1. Effects of soil compaction

3.1.1. Reduced hydraulic conductivity

Soil with hydraulic conductivity of 21.3 mm d^{-1} (normally compacted soil) and 5.5 mm d^{-1} (heavily compacted soil) was simulated over a 30-year period (1988-2018), with the soil moisture content (m_a) determined. Two thresholds for fieldwork were included in the vehicle system model, one for general tillage and one for ploughing. If the soil had lower m_a than the trafficability threshold, the tractors were able to perform the selected operations in the field without damaging the soil. The results showed that with less compacted soil, the average time suitable for ploughing increased from 73% to 82% and the average time suitable for general tillage increased from 48% to 49%, i.e. there was a greater effect on ploughing than general tillage (Fig. 3). However, the greater difference for ploughing had a relatively small effect on overall performance of the system, as much more time was spent on general tillage and ploughing had a wider allowed window of operation. In addition, ploughing was the last operation before the season end for all crops except winter wheat and was therefore less time-critical than other operations.

3.1.2. Delay and changes in trafficability

Fig. 4 shows the time taken to complete all assigned operations in a certain growing season and the fraction of total time required by each operation. Soil compaction caused an increase of 1-3 days over the entire working year, mainly due to decreased saturated hydraulic conductivity leading to longer waiting times for favourable in-field driving conditions. The start of the time-critical spring season was delayed by on average 1.2 days by soil compaction, but this change was less than the variation between years and was assumed to have had a minor effect on the driveability and performance of the vehicle system. The autonomous diesel scenarios all had a significantly lower time requirement, 43-50 days compared with 96 days, but spent a higher proportion of total time working, 37-40% compared with 19% for the manned scenario. It is important to note that the absolute amount of time required to perform fieldwork was similar for all scenarios, but the total time varied as non-productive time (resting time for operator, charging, farm-to-field transport) varied from scenario to scenario. The fraction of time spent waiting for drier fields (denoted "weather" in the figure) remained fairly constant between the scenarios at 49-57%, and the decrease in hydraulic conductivity in compacted scenarios had only a minor effect on the value.

The electric vehicle scenarios generally had a higher time requirement than their diesel counterparts, but showed similar working capacity to the manned diesel scenario, both in overall time and in the time-critical spring season. They had a lower work rate than the top diesel system, but still showed adequate rate of work and the fraction of time spent on fieldwork was similar to that for the manned diesel

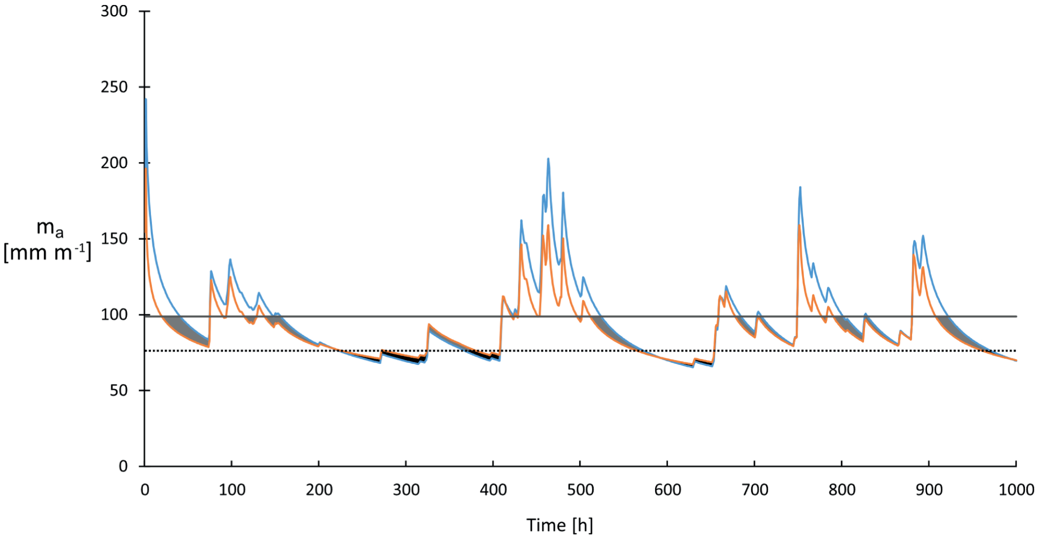

Fig. 3. Soil moisture content (m_a) during the first 1000 h of the growing season in 2016. Two values of soil saturated hydraulic conductivity are shown, for heavily compacted soil (K_{sat} =5.5 mm d^{-1}, blue line) and normally compacted soil (K_{sat}=21.3 mm d^{-1}, orange line). The trafficability limits for general tillage (black dotted line) and ploughing (grey solid line) are indicated. Differences between the two compaction scenarios are shown in grey (for ploughing) and black (for general tillage).

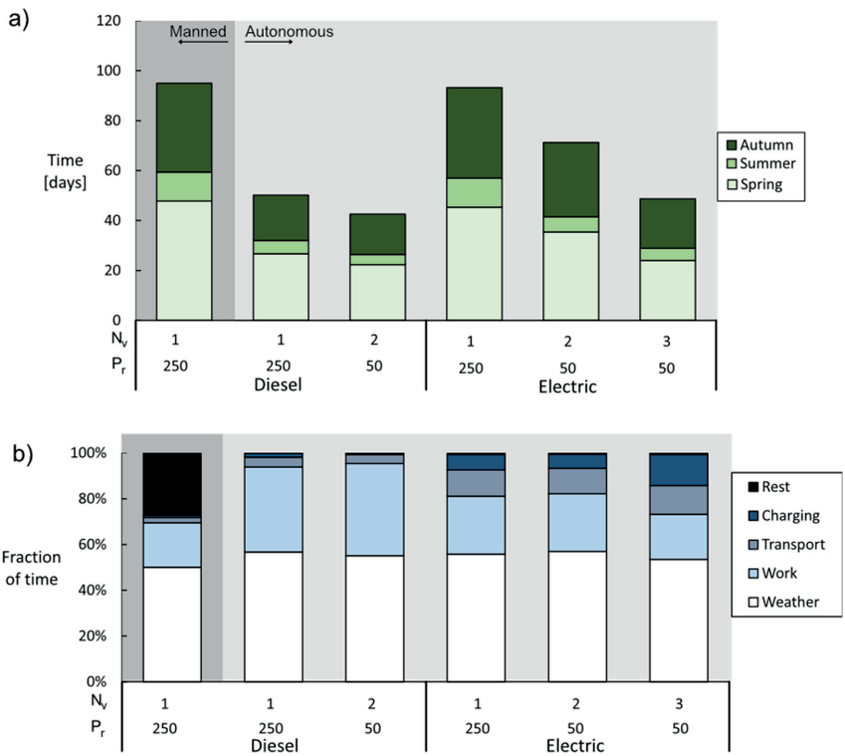

Fig. 4. Results of scenario analysis for six scenarios differentiated by number of vehicles (N_v) and rated power in kW (P_r). (a) Length of working periods, with the conventional diesel scenario serving as an estimate of adequate capacity, and (b) fraction of time spent in different operational modes. All values are 11-year averages (2008-2018). Manned (10 h d^{-1}, dark grey) and autonomous (24 h d^{-1}, grey) operation are indicated as background fields.

system, which served as a baseline for adequate capacity (Fig. 4).

3.1.3. Reductions in crop yield

The yield loss and average yield for the different cereal crops in the system are shown in Fig. 5. The reductions in crop yield calculated based on values in Keller et al. [2], assuming a 8% yield loss, were converted into cost normalised per hectare of arable land and compared with literature values (Table 3).

3.1.4. Increased fuel use due to higher soil density

Dynamic discrete-event simulation of the vehicle system showed that for the conventional diesel tractor, the increased soil compaction caused an increase of 29% in both energy consumption and fuel cost, due to the increased energy use for tilling in heavily compacted soils. For a battery-driven tractor of the same rated power and general weight, fuel use increased by 30%.

3.2. Economic impact

The combined effects of soil compaction varied for the different vehicle systems and individual effects also affected different parts of the cost analysis. Decreased hydraulic conductivity increased the amount of time required to perform all field operations, thus increasing the operator costs and the timeliness cost (the cost of not establishing the crop at the optimal time).

For the diesel scenario, the cost difference between normally and heavily compacted soil was 78 € ha^{-1} y^{-1}, with most of the cost coming from yield loss (78% or 60.4 € ha^{-1} y^{-1}) and increased energy use (22 % or 17.1 € ha^{-1} y^{-1}). Increases in timeliness and operator costs were close to negligible. For the scenario with an electric tractor of the same size and power, the cost of soil compaction was 71 € ha^{-1} y^{-1}, divided into 85% yield loss, 12% increased fuel use and 3% timeliness cost.

These values were used to calculate total annual cost of the systems (Fig. 6). The annual cost varied greatly between the different scenarios, with the heavier vehicles having the highest annual costs. The 250-kW diesel tractor had the second highest cost, 385 € ha^{-1} y^{-1} (77,000 € y^{-1}), with 78 € ha^{-1} y^{-1} or 20% being attributable to soil compaction through higher fuel use or yield losses. Making this tractor autonomous reduced this cost to 306 € ha^{-1} y^{-1}, mainly by reducing the operator and timeliness costs. The highest cost was seen for the 250-kW electric tractor, 421 € ha^{-1} y^{-1} (84,163 € y^{-1}), of which 71 € ha^{-1} y^{-1} (17%) was attributable to soil compaction (Fig. 6).

The electric scenarios generally had a higher annuity, as they needed higher initial investment, but in return had lower maintenance and fuel costs. Compared with the diesel scenarios, the electric scenarios with smaller vehicles showed a 46-62% reduction in fuel costs (Fig. 6). The scenario with two 50-kW electric autonomous tractors had an annual cost of 258 € ha^{-1} y^{-1}, with annuity and timeliness being the main costs. The scenario with three 50-kW vehicles had a cost of 273 € ha^{-1} y^{-1}, reducing the timeliness cost compared with the two vehicle system by

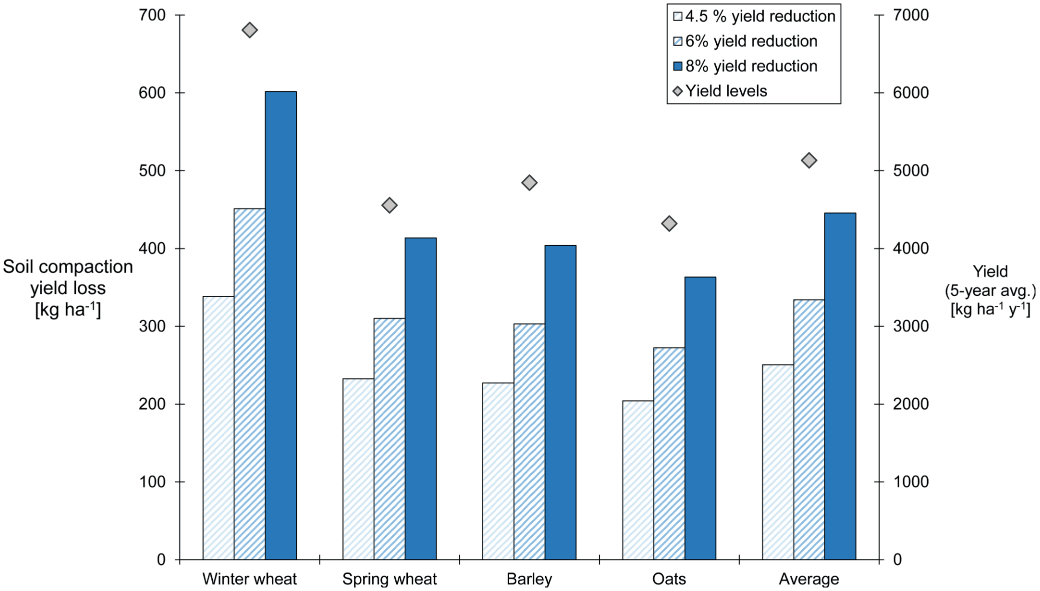

Fig. 5. Yield loss levels due to soil compaction (left axis), for different cereal crops and for all four cereal crops in the system studied, based on yield loss levels from the literature [2,18]. The 8% loss assumed in simulations is shown as solid blue bars, while alternative levels are shown as cross-hatched bars. Actual yield levels (right axis) are shown as grey diamonds.

Table 3
Cost normalised per hectare of arable land of simulated yield losses due to soil compaction for the individual cereal crops and for all four cereal crops in the system studied. Proposed yield loss levels from the literature [2,18] are shown for comparison. Values from Table 2 were used in the calculations. The values from Graves et al. [18] are adjusted for inflation.

Yield reduction level	Cereal crop					Notes
	Average, all cereal crops	*Winter wheat*	*Spring wheat*	*Barley*	*Oats*	
4.5 % [€ ha^{-1}]	34.0	46.6	33.3	31.6	24.4	Suggested value for light soils [18]
6% [€ ha^{-1}]	45.3	62.2	44.5	42.1	32.5	Swedish average for 25-40% clay [2]
8% [€ ha^{-1}]	60.4	82.9	59.3	56.1	43.3	Suggested value for >40% clay [2]
Average for all cereals [€ ha^{-1}]	49.8					[18]

increasing the annuity. Compared with the conventional diesel scenario, this represented a cost reduction of 29%. The lowest cost was seen in the scenario with two small, light autonomous diesel tractors, which were light enough not to incur any penalty from soil compaction and did not have the large initial investment needed in the electric scenarios. They had a cost of 196 € ha^{-1} y^{-1}, a reduction of 49% compared with the conventional diesel scenario.

3.3. Life cycle assessment

The LCA results showed that the electric, autonomous vehicle systems had a lower impact in terms of GWP, human health, ecosystem impact and resource scarcity than the diesel vehicle, except for the 50 kW diesel vehicle in the “ecosystem impact” damage category. The conventional 250 kW diesel scenario (which included soil compaction) had GWP of 270 kg CO_2eq ha^{-1} y^{-1}, of which 241 kg CO_2eq ha^{-1} y^{-1} (89%) originated from the fuel. In particular, 26% of the total GWP impact was due to increased fuel use because of soil compaction. The smaller diesel vehicle system with two 50-kW tractors and normally compacted soil had GWP of 188 kg CO_2eq ha^{-1} y^{-1}, of which 170 kg CO_2eq ha^{-1} y^{-1} (90%) derived from fuel use. The total GWP for the electric vehicles was 77-143 kg CO_2eq ha^{-1} y^{-1}, of which 55-67% was due to fuel use in the electric vehicles (Fig. 7).

The general trend was the same for the three damage categories, with the electric scenarios having lower impact overall but a higher impact in the vehicle category, mainly because of battery manufacture (Fig. 7). Soil compaction led to a 26-27% increase in the damage categories for the 250-kW diesel tractor. The 250-kW battery-electric tractor had a larger impact than the system with multiple 50-kW tractors, because of higher material requirement during manufacture and increased energy use due to higher weight. In the electric vehicle scenarios, soil compaction was an increase of 5-12% for the different damage categories, which was lower than for the corresponding diesel scenario.

To accommodate yield loss as an effect of soil compaction, the results were also expressed normalised on the total amount of grain produced during the life cycle, assuming a constant yield based on the 5-year average used in this study (2017-2021). The effects included both the increased fuel use that comes with performing tillage on compacted soil and the reduction in yield levels (Fig. 8). The conventional diesel tractor scenario showed an increase in GWP from 0.039 to 0.057 kg CO_2eq kg_{grain}^{-1} when factoring in soil compaction. This can be compared with

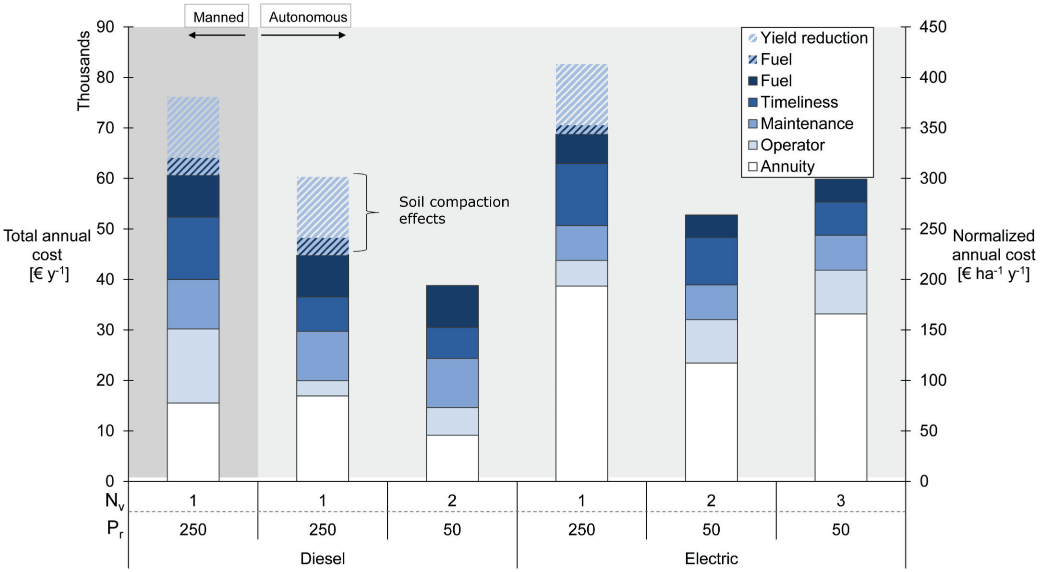

Fig. 6. Total annual cost of the different scenarios, distributed per category of costs (left axis) and normalised to annual cost per hectare (right axis). The annuity is divided over the lifetime of the tractor (generally 15 years) and all other values are 11-year averages (2008-2018). Battery depreciation and replacement are included in the annual cost. Scenarios are differentiated by number of vehicles (N_V), rated power (P_r) and fuel (diesel, electric).

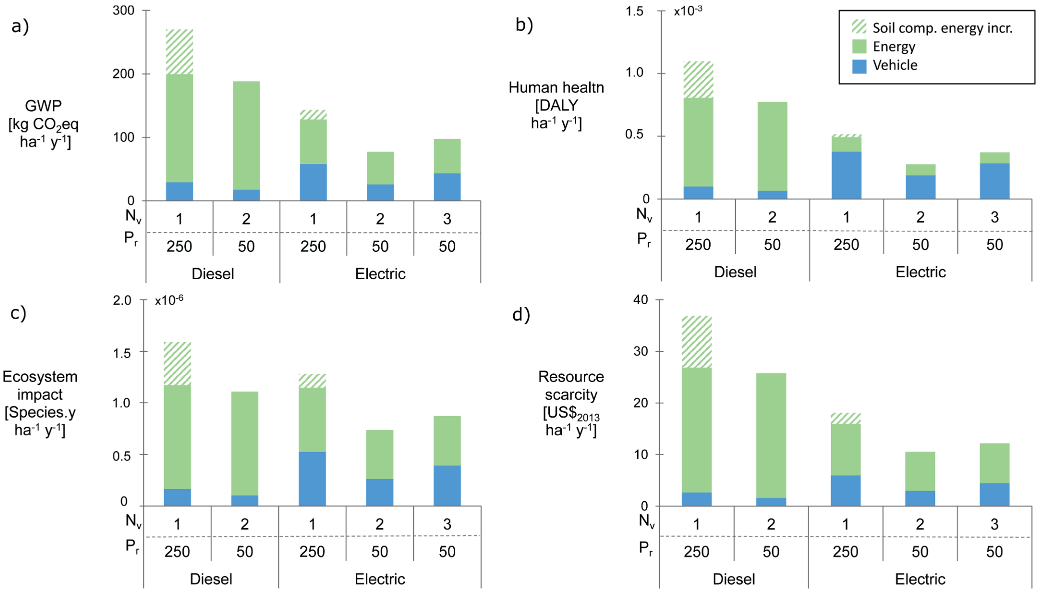

Fig. 7. General life cycle assessment (LCA) results for different scenarios, showing (a) the midpoint characterisation factor global warming potential (GWP) and the damage categories (b) human health, (c) ecosystem impact and (d) resource scarcity. Scenarios are differentiated by number of vehicles (N_V), rated power (P_r) and fuel (diesel, electric). The fuel use increase due to soil compaction (green diagonal stripes) was calculated from values in Lindgren et al. [38]. End-of-life is included in the "Vehicle" category.

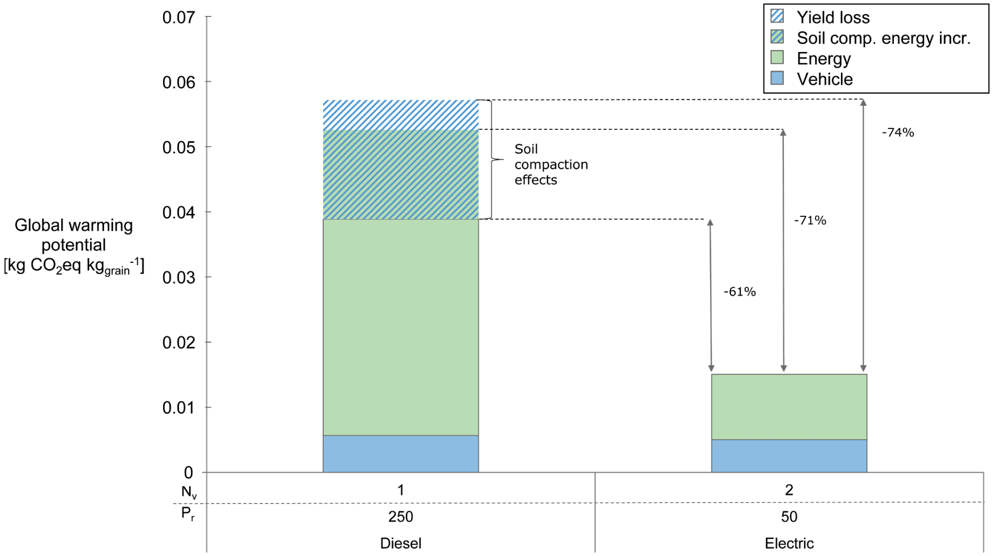

Fig. 8. Life cycle assessment (LCA) results normalised on weight of harvested grain, based on prediction of constant yield at the 5-year average for Sweden (2017-2021). Global warming potential (GWP) reductions compared with the diesel-based scenario are indicated by arrows. Scenarios are differentiated by number of vehicles (N_V) and rated power (P_r).

0.015 kg CO_2eq kg_{grain}^{-1} for the electric tractor scenario.

3.4. Sensitivity analysis

The result of the sensitivity analysis are shown in Table 4. Multiple factors contributed on similar levels to the annual costs, with vehicle lifetime and operator cost both making relevant contributions. Factors connected to soil compaction had a noticeable, but not major, impact. The direct increase from a +10% yield level change was +2% of the total costs, or 1209 € y^{-1}. The indirect changes can be seen in the energy use, where fuel showed higher sensitivity for the diesel scenario than the electric scenario while being on the same level as other factors.

The factor with the highest impact on GWP when changes were simulated was fuel energy use, where a change of +10% in fuel energy use or fuel energy impact resulted in a GWP increase of +7% for the electric tractor scenario and +9% for the diesel scenario. As this was an indirect effect of soil compaction, it is relevant and had a higher impact than other factors considered relevant in electric machine analysis, such

Table 4
Results of one-at-a-time parameter change sensitivity analysis of scenario costs and global warming potential (GWP). The electric scenario refers to a system with two autonomous 50-kW electric vehicles, while the diesel scenario refers to a system with one manned 250-kW diesel-powered vehicle.

		Base value $P(V_0)$	Absolute change Δ_V		Absolute sensitivity S_A		Relative sensitivity S_R	
	Parameter change		**-10%**	**+10%**	**-10%**	**+10%**	**-10%**	**+10%**
Annual cost	*[€ y^{-1}]*							
Electric	Operator time	51,599	-859	858	-2%	2%	0.17	0.17
	Battery cost	51,599	-500	498	-1%	1%	0.10	0.10
	Energy use	51,599	-446	445	-1%	1%	0.09	0.09
	Electricity price	51,599	-446	445	-1%	1%	0.09	0.09
	Vehicle lifetime	51,599	1778	-1457	3%	-3%	-0.34	-0.28
Diesel	Operator time*	80,425	-1468	1469	-2%	2%	0.18	0.18
	Yield loss level	80,425	-1208	1209	-2%	2%	0.15	0.15
	Energy use	80,425	-1514	1515	-2%	2%	0.19	0.19
	Diesel price	80,425	-1514	1515	-2%	2%	0.19	0.19
	Vehicle lifetime	80,425	1282	-1049	2%	-1%	-0.16	-0.13
GWP	*[kg CO_2eq ha^{-1} y^{-1}]*							
Electric	Electricity use/impact	77.3	-5.2	5.1	-7%	7%	0.67	0.67
	Battery impact	77.3	-2.1	2.1	-3%	3%	0.27	0.27
	Vehicle production impact	77.3	-2.6	2.6	-3%	3%	0.3	0.3
	Recycling level	77.3	0.4	-0.5	1%	-1%	-0.06	-0.06
	Vehicle lifetime	77.3	2.9	-2.3	4%	-3%	-0.37	-0.30
Diesel	Diesel use/impact	269.9	-24.0	24.1	-9%	9%	0.89	0.89
	Total vehicle production impact	269.9	-2.9	2.9	-1%	1%	0.11	0.11
	Vehicle lifetime	269.9	3.2	-2.7	1%	-1%	-0.12	-0.10
	Yield loss level [kg CO_2eq kg_{grain}^{-1}]	5.7×10^{-2}	-4.9×10^{-4}	5.0×10^{-4}	-1%	1%	0.09	0.09

as vehicle production, battery impact and fuel price.

To measure sensitivity to changes in hydraulic conductivity, a simulation was performed using a range of values found in the literature and trafficability (when it is "safe" to work on the field) was assessed for ploughing and general tillage with a manned 250-kW diesel tractor. The total time required, a nominal indicator of performance, was also assessed for an autonomous diesel vehicle, to ensure that field status was the only restricting factor. The results indicated a fairly small impact on trafficability at Ksat levels above 2.5 mm m-1 (Fig. 9).

4. Discussion

4.1. Goal, aim, scope

Tillage machine systems of different sizes and with different fuels were simulated and analysed in this study, with specific focus on the effects of soil compaction during tillage. Previous studies of similar systems have focused on performance [25], economics [9] and environmental effects [11]. Improved soil health has been suggested as a beneficial side-effect of the reduced vehicle weight possible with self-driving vehicles, but has rarely been the main focus of studies. This is despite one of the EU biodiversity goals for the New Green Deal being healthy soils through preserving land resources and addressing soil degradation on an international scale [58]. Therefore studies quantifying the potential benefits of systems allowing reduced vehicle weight are relevant.

A choice was made in this study to perform several kinds of analysis in parallel, in order to get a broader understanding of effects, benefits and challenges. When performing analysis on technological systems such as machinery, some choices can optimise one of the goal parameters by omitting others, e.g. an economically beneficial choice can have a large negative environmental impact that may be overlooked if the study does not include an environmental analysis. By studying several goal parameters, more complete and accurate analysis is possible and more informed recommendations can be made.

The focus in this study was on the machinery system and on-site effects of soil compaction, which meant excluding some of the effects of soil compaction, such as effects pertaining to fertiliser use, biological effects and N_2O emissions. Although these are doubtlessly impactful, it is difficult to separate them from other field effects, quantify them and allocate them to soil compaction. Soil compaction is a wide and complex area of research, so a decision was made to focus on certain impacts identified as important in the literature, mainly reduced trafficability, yield loss and increased fuel use. However, comparison of the results with literature values was still possible, as discussed later in this section. Another decision was to limit the scope to a specific scenario of cereal farming on clayey soil in Sweden. The effects of soil compaction differ with soil type, and therefore the choice of soil type is impactful. This means that, unlike in some previous studies [2,16,18], the results are limited to a specific scenario rather than generalised for a large region, nation or crop type. They should thus be seen as giving an example of soil compaction dynamics in vehicle systems analysis, and not as a generally applicable rule. The result is also weather dependent, with 11 years of Swedish weather data used for precipitation. The result is therefore spatially dependent.

4.2. Soil compaction

Use of lighter vehicles was the main source of soil compaction avoidance and alleviation analysed in this study. The main solutions proposed in the literature are lowering axle pressure, adding additional wheels, using tracks instead of wheels, minimising the number of passes or limiting traffic to predetermined lanes (i.e. controlled traffic farming) [19,43,44]. All of these solutions have been well studied, but all are based on the assumption that tractors need to be large and heavy to give high productivity, which has been proven to be true over history. Batey

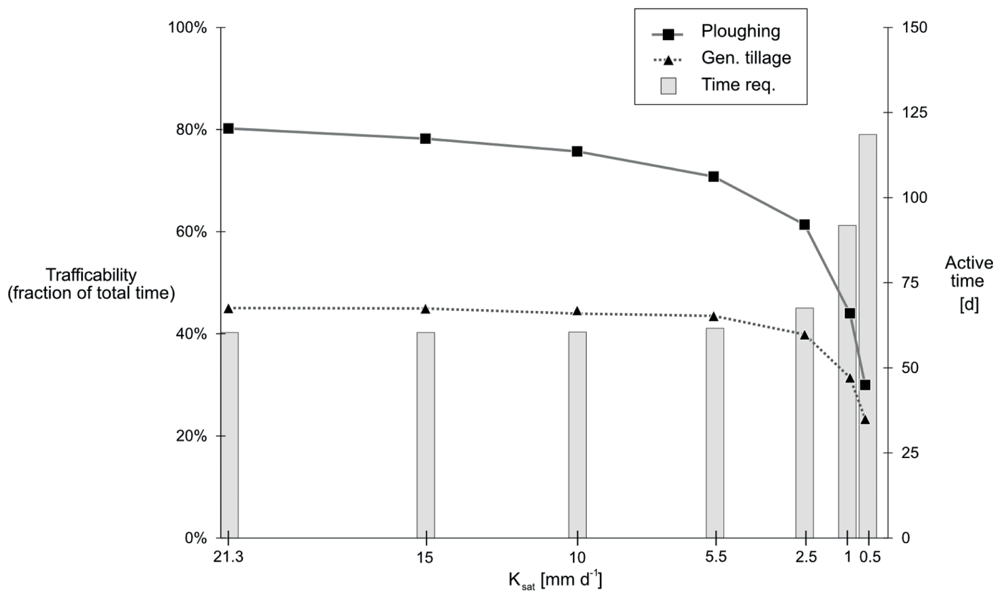

Fig. 9. Simulated trafficability and active time required for a manned 250-kW diesel tractor at different soil saturated hydraulic conductivity (K_{sat}) values. Trafficability (left axis) for ploughing (■) and general tillage (▲) is shown as a fraction of total time during the growing season (machine-independent). Active time required (grey bars, right axis) is also shown for an autonomous 250-kW diesel tractor.

[44] calls the high weight of modern tractors "inevitable and unavoidable", due to current farming economics and practices, as it is the best way to ensure high productivity from a single driver. If lighter vehicles were made more feasible through vehicle autonomy and fuel change, as assumed in this study, that would open up new avenues for soil compaction avoidance.

According to Hamza and Anderson [15], topsoil compaction is related mainly to ground pressure and can therefore be lowered by increasing the tyre-soil contact area using treads or multiple wheels, while subsoil compaction (the focus in this study) is related to the axle load and therefore vehicle weight. An additional important factor is the number of passes, where Hamza and Anderson [15] and Seehusen et al. [59] notes that the first pass cause a major part of the topsoil compaction, but a high number of passes reduces the benefits of lighter vehicles. This is relevant as a lighter vehicle might lead to a higher number of passes, and electric vehicles might increase the traffic on field due to more frequent refuelling. However, this was not included in the study, as the focus was subsoil compaction. Topsoil compaction can have more severe effects on e.g. crop yield than subsoil compaction [21,41] but was outside the scope of this study, which examined long-term differences of a change in machine system. It was assumed that temporary topsoil compaction would still occur, but that it was reversible within a short time for both vehicle systems, while only the heavier vehicle systems would cause irreversible or long-term soil compaction.

A large proportion of arable land is already experiencing soil compaction [18], so data on yield levels and vehicle energy use already implicitly include losses from soil compaction, preventing comparison to a vehicle system with no soil compaction effects. This makes comparison difficult. Keller et al. [2] argue that most field trials compare normally compacted soils with experimentally compacted soils, since most agriculturally managed soils are at least partly compacted. Therefore yield penalties identified in the literature derive from further compaction of already compacted soil and not compaction of uncompacted soil [2]. For ease of presentation and for comparison with literature data, this study made the same assumption and used normally compacted soil as the baseline, with the term heavily compacted soil used for further negative soil compaction by heavy vehicles. This was done because the soil compaction resulting from normal agricultural traffic is hard to avoid, while further soil compaction might be alleviated by different vehicle or management choices.

The level of yield loss due to soil compaction was shown to have a relevant impact on system costs and environmental impact in this study. The literature reports a range of values for yield losses due to soil compaction, most often 4-10% but sometimes losses of 15-16% [16,19]. Graves et al. [18] proposed a value of 4-5% yield loss on British arable land due to soil compaction, which is close to values for Swedish arable land in Parvin et al. [60]. For long-term soil compaction on Swedish soil, Keller et al. [2] reported a yield loss of 8% on clay-rich soil (clay content $>$ 40%), and 6% as a Swedish average. Sonderegger et al. [22] found similar results for soil worldwide, with a 5.5% yearly yield loss for small machines, 8.0% for medium and 9.3% for large. Many factors influence the level of yield loss, but there is agreement in the literature that the loss is non-negligible. Values from the literature used in this study were within the range reported in corroborating sources (Table 3). Thus the 4.5% yield reduction reported for general or light soils for winter wheat [2,18,60] matched the monetary value proposed by Graves, et al. [18] of 49.8 € ha^{-1}. The yield reduction levels proposed by Keller et al. [2] for soils with higher clay content showed a higher monetary loss, but were relevant to the present analysis as Swedish arable soils commonly have a high clay content. For all cereal crops apart from winter wheat, the economic loss at 8% yield reduction was relatively close to the value in Graves et al. [18] and can assumed to be in line with the literature.

Changes in saturated hydraulic conductivity (K_{sat}) and corresponding effects on field trafficability were studied using values and assumptions made in [17]. It was found that the resulting changes in trafficability effect had a minor impact on the economic and performance indicators studied and were not significant, even at large simulated changes in K_{sat}. Poor trafficability has been identified as a potentially significant problem of soil compaction, along with increased risk of flooding [43,44]. In modelling a constant value of K_{sat} is commonly used, but in field trials K_{sat} has been shown to vary significantly between and within fields, making accurate simulation difficult [61]. Very large decreases in K_{sat} (by a factor of 2-28) have been reported [2], suggesting that our estimate of a roughly four-fold reduction might have been conservative and that larger reductions in K_{sat} might be possible in certain situations. Typical K_{sat} values in literature are varied, with 21.3 mm d^{-1} in Witney [34], 74-108 mm h^{-1} in Keller et al. [17] and 20-200 mm d^{-1} in Horn and Fleige [42]. In addition, Lebert et al. [62] states that K_{sat} <100 mm d^{-1} is one indication of harmful soil compaction. However, for the assumed vehicle weights and cropping system, the chosen value of K_{sat} can be assumed to be realistic, albeit low. . Further simulations indicated that lowered K_{sat} had limited effect on the outcome until the level fell below 2.5 mm d^{-1}, when the impact on trafficability became significant (see Fig. 9). In addition, vehicle capacity in the different scenarios was generally well able to handle some extra delay, and it was assumed that the results were adequate. However, soil compaction caused by operations during non-ideal trafficability (i.e. wet fields) should be included in future studies.

4.3. Economics

The total economic difference between the conventional diesel tractor scenario and the main electric tractor scenario was 112 € ha^{-1} y^{-1} in total and 34 € ha^{-1} y^{-1}, in favour of the electric tractor, when disregarding soil compaction effects (Fig. 6). The self-driving electric tractor scenario was shown to be economically competitive with conventional diesel tractors, and including soil compaction made the difference significant in favour of the electric system. A cost comparison by Gao and Xue [63] on transforming conventional tractors to electric found that the electric tractor had 60% of the life cycle cost of the conventional tractor, compared with 71% in this study. An analysis of conventional tractors against autonomous electric tractors by Lampridi et al. [10] produced results favouring the conventional system, but on reducing the recharging times and operator time to values closer to those assumed in this study, the difference between the scenarios was reduced and favoured the electric tractor system in some cases. Lampridi et al. [10] concluded that the high number of assumptions and uncertain estimations make it difficult, although not impossible, to draw conclusions from cost comparisons between field machinery systems. The lowest cost was found to be the lighter, autonomous diesel tractors at 196 € ha^{-1} y^{-1}, as they avoided the negatives of soil compaction as well as the heavy investments of the electric systems, showing how soil compaction alleviation and vehicular autonomy can be economically competitive independent of the electric driveline.

The soil compaction cost for the 250-kW diesel tractor scenario was 78 € ha^{-1}, with 78% from yield loss and 22% from increased fuel use (Fig. 6). Similarly, in Graves et al. [18] the on-site cost of soil compaction was found to be 62.3 € ha^{-1} y^{-1} (adjusted for inflation), with diesel use constituting 8% (5 € ha^{-1} y^{-1}), fertiliser losses 12% and crop productivity losses 80%. Chamen et al. [19] estimated that the increase in gross margin for winter wheat was 78 £ ha^{-1} (91 € ha^{-1}) on reducing ground pressure (an effect of reduced weight) and 117 £ ha^{-1} (136 € ha^{-1}) on introducing controlled traffic farming. Both values are reasonably close to those in this study, although the distribution of costs varied slightly and fertiliser losses were not calculated. This supports the hypothesis that lower vehicle weight leads to improved economic performance. Graves et al. [18] divided the cost of soil compaction into on-site cost (40%) and off-site cost (60%). Parvin et al. [64] also suggested that the majority of the soil compaction cost was from off-site effects. The effects determined in this study were mainly on-site costs, as they related more directly to the scope of the study, and were found to comprise 80% crop productivity losses, 12% fertiliser losses and 8%

additional fuel use. The fuel used increased cost by 29-30%, which is higher than the 8% presented in Graves et al. [18]. Reasons for this include the omission of fertiliser losses and the clay-rich soil used in this simulation compared with the range of British soil types (including peat soils) investigated by Graves et al. [18], where peat was found increase energy use by only 29%, compared with 87% on clay soils.

An assumption was made in the economical calculation that apart from the machinery costs specifically stated; many factors (housing, insurance, implement, harvest and inputs among others) were assumed similar in cost between the scenarios and not explored in detail [9]. It was assumed that in every scenario the machine was a new acquisition, which would have extended to the implements. In reality, implements can often be re-used and switching machine sizes leads to a need to acquire new implements. According to Maskinkalkylgruppen [65], it is in general cheaper to rent or buy two implements for 50 kW tractors than one implement for a 250 kW tractor. New implements for two 50 kW tractors would total 50-75 € ha^{-1} [65] with no extra cost to the conventional tractor system, if implement re-use is assumed. With this cost included, the 50 kw electric tractor system remains economically competitive.

A highly significant assumption in this study was that a manned tractor can be replaced with several smaller autonomous machines. Recent developments justify this assumption [24,66,67] and cost reductions in cereal production of 19-24% have been reported [10,24], compared with a 38% reduction in this study. However, there is still much uncertainty regarding the level of manual oversight such a system requires and who the overseer will be. The rate of oversight and the operator cost have been shown to have a strong effect on the annual cost [9,10]. In this study, based on Lagnelöv et al. [9], it was assumed that an autonomous system would need oversight during 10% of charging/-refuelling, 20% of fieldwork and 30% of road transport, with the service paid per hour. Lowenberg-DeBoer et al. [24] assumed a 10% oversight rate performed by a full time employee who also had other tasks on the farm, with the option of hiring extra labour on a per-hour basis. Lampridi, et al. [10] assumed full oversight, but with 50% labour cost. A preferred method has not been established, so future research must remain flexible in deciding management strategies and cost assumptions for autonomous agricultural vehicles.

4.4. LCA

A number of LCAs have been performed on cereal production, but it was difficult to find studies using similar system boundaries as this study, i.e. mainly focusing on machinery use. Literature values for Swedish wheat production indicate an environmental impact of 0.22-0.70 $CO_2eq\ kg_{grain}^{-1}$ [68–70], with 0.63 CO_2eq per kg proposed by Moberg et al. [69] as an average value for cereals. In several studies, the machinery system and energy use have been found to contribute around 5-20% of the total GWP impact in grain production [69–72]. This represents a range of 0.011-0.14 kg $CO_2eq\ kg_{grain}^{-1}$, with an average value of 0.063 kg $CO_2eq\ kg_{grain}^{-1}$. This is close to the GWP of 0.057 kg $CO_2eq\ kg_{grain}^{-1}$ found in LCA in the present study (Fig. 8).

In addition, Moberg et al. [69] report a value of 0.07 kg $CO_2eq\ kg_{grain}^{-1}$ for vehicle production and use. For a system with similar system boundaries in this study, GWP was 0.057 kg $CO_2eq\ kg_{grain}^{-1}$ of which 0.018 kg $CO_2eq\ kg_{grain}^{-1}$ resulted from soil compaction. This can be compared to the 0.015 kg $CO_2eq\ kg_{grain}^{-1}$ for the electric tractor scenario. Lovarelli and Bacenetti [73] report values of 190-205 kg $CO_2eq\ ha^{-1}$ for grain production, compared with 269 kg $CO_2eq\ ha^{-1}$ in this study (200 kg $CO_2eq\ ha^{-1}$ on normally compacted soil) (Fig. 7). Since fuel energy was the main contributor to the environmental impact for GWP and for the three damage categories considered, validating fuel consumption is an indirect way to validate the LCA results. Fuel use for the diesel case was 54 L ha^{-1} for normally compacted soil and 76 L ha^{-1} for heavily compacted soils, which are realistic findings compared to literature values of 44-60 L ha^{-1} [36–38] and 66-72 L ha^{-1} for Swedish cereal crops [74]. This indicates that the results in this study linking lower vehicle weight to reduced environmental impact are reasonable. The electric tractor scenario showed potential for significantly lower GWP than previously established.

4.5. Further research & recommendations

Some factors shown to be impactful in previous agricultural LCAs of cereal production were outside the scope of this study. These include N_2O emissions, land use, fertiliser and pesticide use, grain transport and grain drying. Some soil compaction effects were also outside the scope of the study, but the results confirmed the importance of including soil compaction in environmental impact analysis and LCAs [13,21]. In fact, the results indicated that a noticeable impact of soil compaction on all environmental impact categories studied (GWP, human health, ecosystem impacts and resource scarcity).

In further research, we recommend including soil compaction in machinery analyses and assessments. If lighter vehicles emerge as a probable technology pathway due to autonomy, the recommended mitigation and avoidance measures listed in the literature need to be re-evaluated. Furthermore, the soil compaction factors omitted in this study should be included in future work on the economic and environmental effects of soil compaction and machinery systems, and in LCAs of grain production.

5. Conclusion

Electric, autonomous tractors makes it possible to replace one heavy machine with several lighter while being economically viable and avoiding further soil compaction. Soil compaction was shown to have economic and environmental impacts, mainly through increased fuel energy use and yield losses. Decreased hydraulic conductivity due to soil compaction had a minor effect on performance and economics and no effect on environmental impact in the scenarios studied.

The economic impacts of soil compaction were non-negligible, increasing the costs by 20% on heavily compacted soil. The environmental impacts were also non-negligible, with soil compaction increasing climate change per kg grain by 46% compared with normal soil compaction. The increase in climate change impact was 26% when calculated per hectare (which disregarded yield loss). The increase was roughly similar (26-27%) for the three damage categories studied (human health, ecosystem impact and resource scarcity). This was mainly attributable to diesel use, which is already a large factor in the environmental impact of agricultural machinery use, and increased energy need from soil compaction, which further increased this impact.

The economic and environmental impacts of further soil compaction were similar in magnitude to those of making tractors autonomous. Overall, soil compaction gave rise to some of the largest impacts in machinery analysis, showing that it should be considered in machinery analysis and calculations.

Compared with a conventional scenario with a heavy diesel tractor and associated soil compaction, electric autonomous tractors with lower vehicle weight reduced operational costs by 29-33%, climate impact by 71-73% and damage category impacts by 54-75%. Soil compaction avoidance alone might not provide a strong enough incentive for a shift to electricity or autonomy but, as an added benefit among others, it provides a strong argument for a technology shift from heavy diesel tractors to lighter, self-driving electric tractors. Soil compaction further amplifies existing trends and including avoided soil compaction in system analysis maximises profitable and environmentally beneficial choices and minimises detrimental choices.

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CRediT authorship contribution statement

Oscar Lagnelöv: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Gunnar Larsson:** Conceptualization, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Anders Larsolle:** Conceptualization, Validation, Writing – original draft, Supervision. **Per-Anders Hansson:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2022.100156.

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In order to reduce agricultural machinery climate impact, electric tractors can be considered due to its high efficiency and lower-impact fuel. Combined with vehicle autonomy, many of the challenges of battery electric drivelines are mitigated with several additional potential benefits. This thesis examines the performance, cost and environmental impact of battery-electric autonomous tractors compared to conventional tractors in a simulated environment based on Swedish agriculture.

Oscar Lagnelöv received his postgraduate education at the Department of Energy and Technology at the Swedish University of Agricultural Sciences (SLU) in Uppsala, Sweden. He holds a Master of Science degree in Energy Systems Engineering from Uppsala University.

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