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Sustainable agriculture by the Internet of Things – A practitioner's approach to monitor sustainability progress

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A R T I C L E I N F O

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A B S T R A C T

Sustainability is a major challenge in agri-food systems. Digital technologies, such as Internet of Things (IoT) hold substantial promises for attaining the sustainability goals of the economy, environment and society at large. However, in practice it is difficult to evaluate to which extent these technologies contribute to sustainable development raising doubts about their impact. This paper demonstrates a stepwise approach that allows for measuring and monitoring IoT contribution to sustainability in a real-life context. The UN sustainable development goals (SDGs) underpin the principles of the approach by a typology and by framing the sustainability impact in terms of business opportunities. The approach has been developed and evaluated by 33 use cases in the EU-funded IoF2020 project. The research illustrates how the measurement and monitoring tool is applied in 5 of these use cases from different agricultural subsectors showing how the approach is applied and validated. The results indicate an overall positive impact of IoT on improving sustainability, although these results are also partly determined by other influential external factors that cannot be easily discerned in a practical situation. The main contribution of this approach is the set of instruments for practitioners to measure and monitor the impact of fast-changing technologies such as IoT to sustainability in a real-life context. This set of instruments can also be used by other stakeholders in large IoT projects where strategic sustainability objectives should be supported by IoT solutions. The stepwise approach is easy to communicate and supports stakeholders such as farmers in decision-making, but also policy makers and investors in funding projects.

1. Introduction

It has been widely argued that sustainability is a major challenge for agriculture and food production. Agriculture is therefore included in the UN sustainability development goals (SDGs) such as Zero Hunger (SDG2), Responsible Consumption and Production (SDG12), Climate Action (SDG13) and Life and Land (SDG15) (Swanson, 2015). Total production and productivity per unit of land must increase while natural resources must be used more efficiently, and waste must be reduced. Pollution and other negative effects must be minimized or reduced to zero.

However, agriculture is a biological process by nature that deals with living organisms, is season- and weather-dependent, often situated in the open air and therefore hard to control. There are several innovation paths to take up these challenges. Science has the potential to develop technologies that can boost productivity whilst addressing resource scarcities and environmental problems. Research findings suggest that digital technologies such as Precision Agriculture, Smart Farming, Internet of Things and Artificial Intelligence in agriculture are key technologies to develop sustainable agriculture (Hrustek, 2020; Jung et al., 2021; Schepers, 2019; Verdouw et al., 2016; Wolfert et al., 2017). This paper focuses on the Internet of Things (IoT) technology.

In IoT, every 'thing' becomes uniquely identifiable and is - ideally real-time - connected through the Internet or other local area networks (Atzori et al., 2010). In an agricultural context, things can be plants, fields, cows, machines, etc. which are connected by all kind of sensors measuring e.g., temperature, humidity, or location (Maraveas et al., 2022; Tao et al., 2021; Tzounis et al., 2017). In different fields of application, IoT solutions connect various things e.g. by soil or plant sensors and local meteorological stations in arable farming, while ear tags, weights, and behaviour-tracking cameras connect things in livestock farming. Through the data that are derived from the things, they can be considered as digital twins of the objects in reality (Verdouw et al., 2021). Beside measuring, things can also be actuators, executing certain tasks e.g., increase temperature in a greenhouse, irrigate a field, feed a cow, etc. Thus, IoT is typically characterized by a sensor-actuator

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network of objects that in some cases can function completely autonomously but are often still controlled through human intervention.

Scholarly literature indicated that there is a clear potential for IoT to contribute to a more sustainable agriculture (Kidd, 2012; Maraveas et al., 2022; Moysiadis et al., 2021; Symeonaki et al., 2017; Talavera et al., 2017). Especially when IoT is considered as an extension of the existing paradigm of Precision Agriculture (Jaiganesh et al., 2017; Javier et al., 2020; Trivelli et al., 2019; Uferah et al., 2019). IoT has the potential to improve agricultural resource use efficiency in general (Alonso et al., 2020; Tao et al., 2021; Verdouw et al., 2016) or more in particular water use (Abioye et al., 2020; Cambra et al., 2018; Carlos et al., 2019; Manuel et al., 2020; Pincheira et al., 2021; Talavera et al., 2017), pest and disease reduction (Bischoff et al., 2021; Sergio Trilles et al., 2019; Yiannis et al., 2017) or energy use and CO2-emission reduction (Chiara et al., 2020; Maraveas et al., 2022). A few references also show how IoT can address sustainability challenges in the whole food supply chain (Paul et al., 2022; Yadav et al., 2020; Zhong et al., 2017) and for smallholder farmers (Antony et al., 2020).

In practice, a more general set of objectives, such as productivity increase, management support or product traceability are considered by firms in agriculture (Tao et al., 2021; Verdouw et al., 2016). Although sustainability itself is often not the primary objective or focus of firms when implementing IoT technologies, it can definitely contribute to the transformation of agriculture into a more sustainable production system as argued in the previous paragraph. However, due to interrelationship between multiple objectives and applied technologies in the real-life context of farming, it is difficult to specifically monitor and evaluate how IoT technology contributes to sustainability. A comprehensive approach to address this challenge is lacking, while sustainability in agri-food business can be considered as an opportunity for new business development. Urged to find sustainability solutions and to manifest sustainability gains of IoT technologies, firms, investors, policy makers and other stakeholders need an assessment tool that relies on quantitative measurable indicators (Braz et al., 2011; Rodrigues et al., 2016).

The objective of this paper is therefore to investigate how IoT technology can contribute to sustainable agriculture by an approach focusing on key performance indicators. This will be done by defining a typology and framework that is used to define and monitor sustainability goals in practice in relation to IoT. This approach is illustrated and validated by several use cases from various agricultural sectors.

2. Research approach

2.1. Multiple case studies

The development of a conceptual typology and framework requires a design-oriented methodology that aims at solving a certain type of problem by constructing a new artefact (Hevner et al., 2004; March and Storey, 2008). The artefact developed in this paper is a conceptual framework for the design and implementation of sustainability in agriculture in relation to IoT. Since this is a new and complex subject, a case study approach is proposed to get a better understanding of such complex phenomena, which cannot be studied outside their rich, real-world context (Eisenhardt, 1989; Yin, 2003). A multiple case study approach is adopted to evaluate the applicability of the presented framework in the context of sustainability and IoT in agriculture.

The study was carried out as part of the European IoF2020 project in close interaction with involved business partners (Verdouw et al., 2017). The main objective of IoF2020 was to foster a large-scale take-up of IoT in the European farming and food domain. The project included 33 IoT use cases that were organized in 5 coherent trials (arable, dairy, fruit, vegetable and meat) that aim to address the most relevant challenges for

Table 1
Description of the selected use cases. The UC-numbering in the names refers to the internal numbering that was used in the IoF2020 project.

Sector	Name	Use case challenge	IoT solution	Sustainability goal
Arable	UC1.1 Within-field management zoning	Defining specific field management zones by developing and linking sensing- and actuating devices with external data	Electro-magnetic soil scanner creates a soil map that is combined with other data and translated by an algorithm into a variable rate application (VRA) map for various purposes (spraying, fertilizing, haulm destruction). Machine-to-machine communication is facilitated by a LoRa (low power wide area) network.	Save resources (pesticides, fertilizers) and therewith costs and protecting the environment by variable rate application targeting the specific spatial and temporal differences between various management zones based on site-specific sensing and monitoring.
Dairy	UC2.2 Happy Cow	Improving dairy farm productivity through 3D cow activity sensing and cloud machine learning technologies	Cows wear a sensor that tracks their movements in 3 dimensions. All data is uploaded to the cloud where artificial intelligence is used to translate the data into insights. The insights are transmitted to the farmer via an app on his smartphone, offering suggestions on how to optimize cow management.	Increase productivity by reduced in-between calving time. Increase cow health and reduce medicine use, in particular antibiotics.
Vegetables (indoor)	UC4.2 Chain-integrated greenhouse production	Integrating the value chain and quality innovation by developing a full sensor-actuator-based system in tomato greenhouses	A web-based decision support system integrates information from greenhouse sensors, field notebook, lab analysis and models. Information on production and management in the whole supply chain is available for end-users to take decisions and to provide value added information related to crop growth, climate and irrigation set points to fulfil quality, sustainability and traceability objectives.	Increase productivity and decrease environmental impact by reduced resource use, based on improved sensing and crop monitoring.
Vegetables (outdoor)	UC4.3 Added value weeding data	Boosting the value chain by harvesting weeding data of organic vegetables obtained by advanced visioning systems	Sensory and camera system in a weeding machine collect crop data, which is uploaded to the cloud. Through image processing, various parameters are determined such as crop size, -health and weed pressure. These data – combined with other data - are used for decision-making at the farm and upwards value chain.	Increase productivity and save (manual) labour by more efficient weeding. Decrease environmental pressure by chemical-free weeding.
Meat	UC5.1 Pig farm management	Optimising pig production management by interoperable on-farm sensors and slaughterhouse data	Individual pig monitoring by sensors that measure feed and water intake, weight gain and climate conditions. Data is translated into a dashboard with analytics, early warnings and predictions in combination with supply chain data.	Increase productivity and decrease environmental impact by reduced resource based on and improved animal sensing and monitoring.

the sub-sector concerned (Verdouw et al., 2019). In total five cases - representative for different agricultural sectors - were selected to illustrate and validate how IoT can contribute to sustainability (Table 1).

More detailed, technical descriptions of these IoT use cases and parameters that were measured can be found in Appendix 1. For more detailed information about these and other use cases, we refer the IoF2020 use case catalogue (IoF2020, 2021) and the IoT Catalogue (IOT Catalogue, 2022).

In the IoF2020 project, use cases followed a multi-disciplinary, collaborative, agile approach that embraces a demand-driven methodology in which end-users from the agri-food business are actively involved during the entire development process aiming at cross-fertilisation, co-creation, and co-ownership of results. The basis of the approach for the use cases is a combination of the lean start-up methodology that focuses on the development of Minimal Viable Products (MVPs) in short iterative cycles and a multi-actor approach that stresses the active involvement of various stakeholders (Ries, 2011). An MVP is a version of a product, or service, with just enough features that can be evaluated by the users. Each MVP after a next cycle adds more features until the stage is reached at which the digital solution is mature and can be introduced at a large scale. To reach that, use cases were actively supported by various disciplines ranging from data science, business modelling, governance, ethics to ecosystem development.

Sustainability management relates to business modelling in particular because nowadays sustainability performance is an essential part of agri-food business. However, the literature on sustainability of IoT in agri-food fails to provide applicable tools that can brace decision-making of practitioners and help them plan investments in sustainable data-driven technologies. The next subsection explains in more details the steps that were taken to monitor and support sustainability development in the use cases.

2.2. Stepwise approach – A practitioner's guideline

A comprehensive monitoring method for sustainability impact measurement is then needed to catch business opportunities and adapt to environmental restrictions that are posed on agriculture. To identify, measure and monitor the impact of IoT in agri-food, we have adopted the main attributes and descriptions of performance measurement suggested by Braz et al. (2011). Rodriguez et al. (2016) suggest a framework that considers all three aspects of sustainability (economic, environmental, social) with a strong focus on economic performance. While the literature often focuses on economic performance measures as the main driver of the businesses, the environmental and social impacts of sustainability receive more priority especially in agri-food systems. Therefore, we have expanded the suggested frameworks towards a five-step method to entail impact assessment in a more holistic way (Fig. 1).

Step 1: Define target sustainability goals

To define the targeted sustainability goals of technological innovations and IoT solutions we used the sustainability-by-design approach suggested by Folke et al. (2016). This approach is based on all 17 Sustainable Development Goals (SDGs) as defined by the UN as a guideline (UN, 2021) (Fig. 2). IoF2020 use cases have been guided through an iterative process to depart from sustainability goals and find the specific targets for their own Key Performance Indicators (KPIs).

KPIs are widely used by firms to assess the impact of businesses and business strategies. KPIs link business strategies with executive actions and by doing so advance innovation activities (Kaplan and Norton, 1996; Neely et al., 2005). KPIs quantify the efficiency and effectiveness of the actions and to evaluate innovation performance (Braz et al., 2011). Thus, KPIs help identify gaps between the current performance and the targeted performance, and monitor the progress towards desired outcome (Muchiri et al., 2010). In the context of this paper, we used KPIs as operational instruments to translate high-level sustainability goals into practical measurable indicators, and by doing so, assess the impact of IoT on sustainability.

Step 2: Define KPIs and functional units

The SDG framework in Fig. 2 has been used by the IoF2020 use cases as a guideline to extract relevant KPIs for the sustainability measurement of the IoT solutions. In addition, based on market insights of the involved stakeholders and expert knowledge, use cases have defined the areas of the highest potential impact. To monitor the progress in a coherent way, KPIs were clearly defined along with the appropriate functional units of measurement. For instance, under SDG8 "Decent work and economic growth", yield increase was taken as KPI, and the indicator has been operationalized as "increase of total amount of crop harvested", and the "animal health and welfare" has been operationalized as "less antibiotics use per animal". Functional units are quantified descriptions of the function of a product or service for all calculations regarding impact assessment (Arzoumanidis et al., 2020). The measurability and quantifiability criteria are best identified through functional units of measurement. In the example of yield increase, the functional unit was "kg/ha/year". Functional units are essential not only for proper measurement, but also for benchmarking and interoperability between software systems.

Step 3: Define baseline and target values

Baseline and target values of KPIs are needed for progress monitoring. Baseline values reflect the performance values without considering the impact of the innovation, *i.e.,* without the use of IoT. To define baseline values, various sources can be used. For instance in IoF2020, use cases used historical data, available literature, statistical data from the region, sector averages, or expert knowledge. Most of the IoF2020 use cases used reference standard practices to define baseline values, which are based on available data of comparable farms/users within the local region. In many cases, reference values were average numbers taken from local statistical reports or historical data of an average performance of certain KPIs in the same farm. Thus, the baseline values reflected the values of standard practices in case no IoT was used.

Target values are quantitative interpretations of strategic goals. The target values help to interpret goals in numbers and monitor how and when the strategic targets can be achieved. To define achievable target values, a critical examination of actions and resources is needed. In the IoF2020 use cases, target values indicated intended sustainability impact goals, *i.e.* impact on economy, environment and society.

Step 4: Identify measurement methods

The right measurement methods, including procedures and data sources for each KPI, determine the accuracy of KPI monitoring. The measurement methods are preferably based on digital systems, e.g. sensory systems, or aggregated data from Farm Management Systems. The measurement methods should be standardized to make outcomes

Fig. 1. Stepwise approach to sustainability impact measurement.

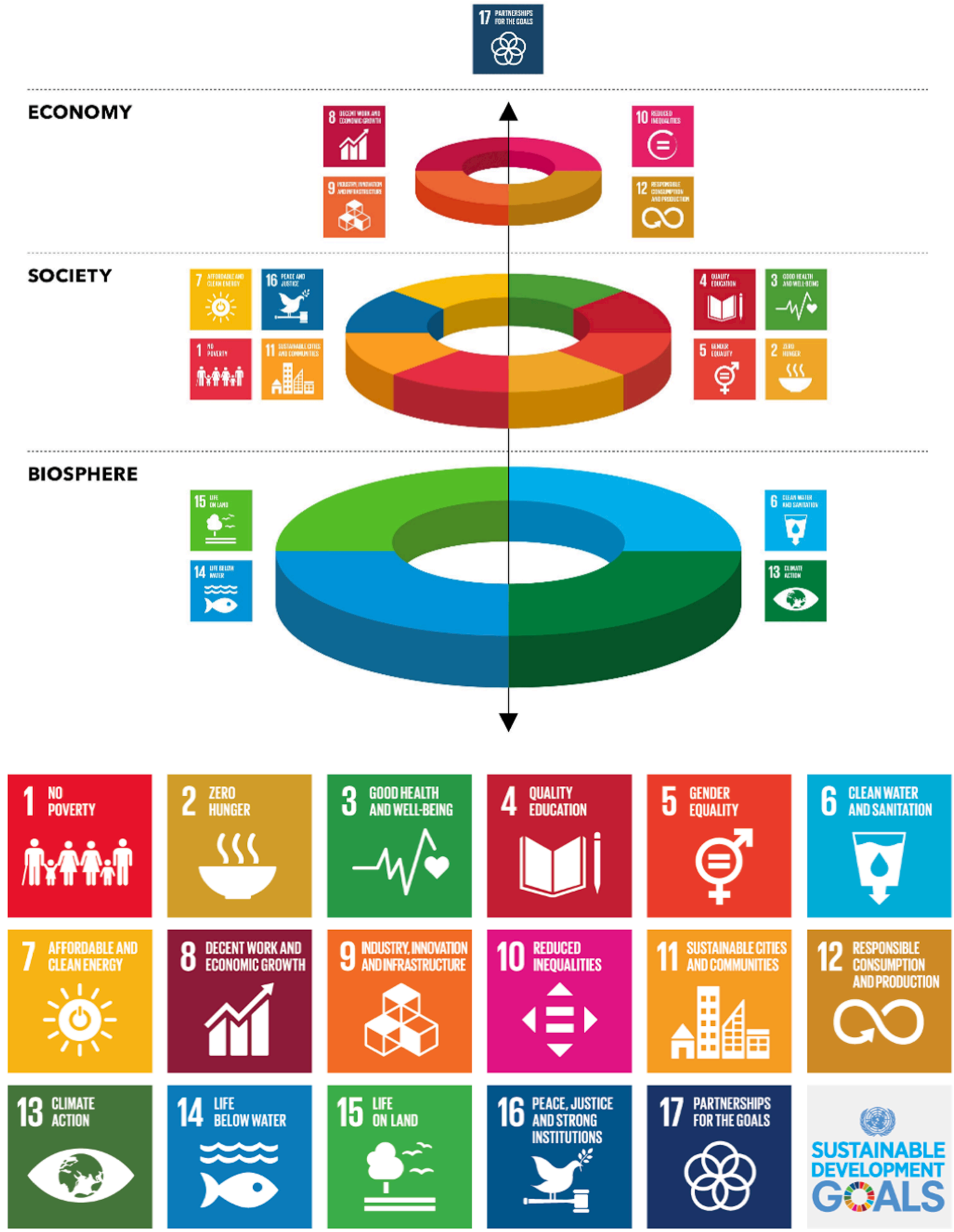

Fig. 2. The global goals for sustainable developments (Folke et al., 2016).

comparable. In case of lacking standard methods the use cases developed their own measurement methods and identified relevant data sources themselves. The frequency of measurement also varied due to sometimes unique nature of the KPIs. For example, milk yield could be measured daily while crop yield was usually measured per harvesting season, which is often once a year. Moreover, the emissions could be continuously measured, but usually only annual measurements were carried out. Thus, due to diversity of use cases, it was impossible to develop one standard measurement method for all use cases. Instead, an approach to find a specific measurement method for every use case and for each KPI was taken.

Step 5: Monitor the progress

Based on the current values of KPIs, use cases carried out a progress analysis to gain understanding of the current position departing from baseline values towards target values. KPI data were collected for the period ranging from 2018 to 2020, via use case progress reports using a KPI data collection template in MS Excel. To show the KPI progress, the annual results were analysed in so-called “heatmaps” showing to what extent the current values of each KPI reached the target value. A colour coding in the heatmaps helped to visualize to what extent the targeted values were real and to what extend the current values deviated from baseline values. The three colours used indicated as follows:

- Red - current value was worse than the baseline value,
- Orange - current value exceeded the baseline value (improvement), but could not reached the target value
- Green - current value reached and exceeded the target value.

This method was especially useful for monitoring the KPIs that had either no appropriate baseline values (alarming when current values exponentially exceeded the baseline) or had too ambitious target values (alarming when current values could not reach the target even when the IoT was fully functional). When the current values deviated from baseline values drastically or when the target values were too ambitious, the use cases were signalled to either adjust the targets or reconsider the KPIs.

To summarise, the stepwise approach provides a guideline to measure and monitor the impact of IoT on strategic goals in sustainability in a real-life context. The guideline is based on existing performance measurement methodologies underpinned by the sustainability development goals. It consists of five steps, of which the first four are preparatory and of a relatively static nature, while the fifth one is dynamic and continuous. The approach can be used by the actors in agri-food IoT ecosystems to plan their investments, measure and monitor the impact, and eventually steer the IoT activities towards the desired sustainability performance.

3. Application of the approach to the use cases

This section illustrates how the approach to measure and monitor sustainability impact by IoT has been applied to the IoF2020 use cases. Section 3.1 provides the results of the first four steps in the context of all 33 use cases of the IoF2020 project by a KPI catalogue. Section 3.2 illustrates the outcome of step 5 by providing sustainability impact measurement examples from the selected 5 use cases.

3.1. KPI catalogue

The key performance indicators that measure impact on the three pillars of sustainable development (economic, environmental, and social), rely on the SDG framework shown in Fig. 2. In step 1, use cases first identified the typology of key performance indicators based on the goals and ambition of the IoT solution. The use cases reviewed, tested and validated the indicators for all three sustainability pillars and have selected the most relevant ones according to their goals and ambitions. In step 2, all 33 use cases identified their preliminary KPIs with the support of IoF2020 business experts. Table 2 presents the identified KPIs categories and indicators grouped for arable, dairy, fruit, vegetable and meat sectors. Note that most of the indicators refer to more than one sustainability pillar. For example, reduction of water use, herbicide use, pesticide use and fertilizer use can be classified under environmental and economic pillar simultaneously, as these indicators reduce environmental negative impact and reduce costs at the same time. Similarly, effective time use is an economic indicator and social indicator at the same time. Efficient time use is needed for the farmers that work under high time pressure. Additionally, the indicators can be interrelated. For example, perceived satisfaction may go down if the performance variables show that the goal has not been reached. Therefore, the indicator may be conditional for the overall outcome.

The preliminary defined KPIs have gone through several tests and changes. Although the KPIs have been defined at an early stage of the project with the expectation to monitor for the upcoming four years, they were adapted responding to the changing technology developments and cyclic nature of the innovation process. Whenever certain innovations and application of technology either changed the focus or the IoT solution shifted towards new market opportunities (usually on the later MVP stages), the KPIs needed adjustments accordingly. KPIs were tested for measurability and quantifiability. Regular interviews and consulting sessions with the use case leaders on KPIs resulted in a shorter list of KPIs of which use cases claimed to be able to measure and provide evidence of impact. However, some preliminary KPIs that sounded socially relevant and could be claimed as impact of a certain IoT solution, had failed to meet measurability and quantifiability criteria. For example, traceability of the product and transparency of the food chain claimed to be impacted by IoT were difficult if not impossible to

Table 2
Categorization of sustainability KPIs by the IoF2020 use cases grouped by subsectors.

Categories	Indicators
ARABLE (9 use cases)	
Productivity	Yield
Efficiency	Work time, Water use, Resource use
Costs	Fertilizer/ Nitrogen/ Fungicide/ Pesticide/ Soil herbicide use, Water use
Quality	Food quality
Soil health	Soil structure, Water balance
Emission	CO2 emission, GHG
Lower Input	Energy use, Fertilizer/ Nitrogen/ Fungicide/ Pesticide/ Soil herbicide use
Ease of work	Effective time use, Time pressure reduction
User satisfaction	IoT user perception in ease of use and usefulness
DAIRY (7 use cases)	
Productivity	Yield per cow, Animal health, Calving interval
Efficiency improvement	Production efficiency
Costs	Return on Investments, Revenue
Quality Improvement	Tractability, Precision of measurement
Waste	Not qualified product
Lower Input	Assets production, Processing/resource use
Animal health and welfare	Mortality, Sickness reduction
Ease of work	Worktime reduction, Improved precision of values
Public health	Food quality, Food safety
FRUITS (6 use cases)	
Productivity	Yield, Throughput speed
Costs	Water costs, Phytosanitary measures, Control costs, Total average costs
Quality Improvement	Shelf-life quality, Proportion of extra olive oil/ campaign
Resource use	Water use, Levels of fertilizer use
Waste	Crop waste during harvest, transport, storage, packaging, Moulds and or wine waste
Emissions and leaching	Frequency of treatment, Energy use, CO2 emission, Nitrogen or pests rests in land / water
User satisfaction	IoT user perception in ease of use and usefulness
Public health	Reduce toxic pesticide exposure
Job quality	High qualified jobs in the sector
VEGETABLES (5 use cases)	
Productivity	Yield, Running hours
Sales	No of machines sold, Turnover
Efficiency	Certification time, Number of human errors
Cost	Production costs, Costs of certification
Quality Improvement	Longer shelf life, Nitrate content
Resource use	Water use, Land use
Pollution/ emission	Pesticide, Fuel use
Satisfaction	Satisfaction of producers
Public health	Level of pesticide active ingredients
User satisfaction	IoT user perception in ease of use and usefulness, Level of satisfaction of auditors
Transparency of food chain	Data available, Trust in the quality of food products
MEAT (6 use cases)	
Productivity	Average daily weight gain, Animal mortality
Efficiency	Better feed convention ration
Costs	Antibiotics and veterinary costs, Water costs
Quality	Boar taint, Uniformity and average weight, Traceability
Animal welfare	Sick animals, Mortality
Resource use	Physical condition, Feed use, Water use
IoT user satisfaction	IoT user perception in ease of use and usefulness, Level of satisfaction of auditors
Public health	Antibiotics use

measure. Sometimes the expected impacts were indirect, such as public health due to e.g., less use of antibiotics and chemical fertilizers, so the direct impact was impossible to measure either. The functional units were defined to compare the current results of the use cases in each indicator with the reference standard practice. Most of the functional units were known from the end-user's accountancy or farm management systems. Nevertheless, attention was required to make sure that the current KPI data, especially if collected by the innovative high-tech devices, were compatible with existing data standards. However, identifying functional units that allowed KPI measurement through the IoT hard- and software in a coherent way and according to the end-users' systems were challenging tasks especially if the innovative IoT devices produced non-standardized data.

Once measurable and quantifiable KPIs per use case were set, step 3 was to define baseline and target values. The IoF2020 use cases were challenged to find appropriate and relevant baseline values, and based on that, to define target values. For instance, if the yield in a reference standard practice was 100 kg/ha/year (in which 100 is the baseline value, kg/ha/year the functional unit), then the target value could be + 10 % (the percentage was dependent on the IoT solution, and the expectations of the use cases to increase yield by using the IoT).

In step 4, the measurement method was identified and KPIs were measured by IoT devices as much as possible to collect the data automatically, without any human intervention. The main source of data were Farm Management Systems that hold aggregated data. Some examples of measurement methods were VRA (Variable Rate Application) task maps, crop recordings, dashboard and farm logs, and time registration tools. For more details on how and what data were measured with IoT we refer to Appendix 1.

3.2. Monitoring progress of sustainability

Once indicators and the functional units were defined, the baseline along with target values were set, and the measurement methods were defined, the 33 use cases started to collect data and monitor the progress of sustainability impact (step 5). The following section presents specific examples of sustainability impact measurement of the 5 selected use cases and illustrates examples of progress that was made.

UC1.1 Within-field management zoning

Table 3 shows the KPIs, functional units, baseline and target values of the KPIs in the within-field management zoning use case. The use case has validated the IoT solution in two validation fields.

Table 3 shows that although the baseline values are different for the two validation fields, the target values are the same. This suggests that independent from how the end-user performs without IoT application, the performance can be increased with a fixed target value.

Monitoring KPIs over the years, the use case has recorded the current values of every KPI. One of the KPIs was the yield. To illustrate this, Fig. 3 shows the yield progress in the period 2016–2020 in validation field 1. It shows that a 6 % increase in yield was achieved in 2020, while the target value was 2 % improvement compared to the baseline. It can be concluded that the result was much better than expected.

Fig. 4 shows a reduction of herbicide use in validation field 1. About 33 % reduction of herbicide use has been achieved in 2020, while the target was −15 %. A clear decreasing line shows the decreasing need for herbicide use over the years.

Similarly, Fig. 5 illustrates the decline of nitrogen use in validation field 1 between 2016 and 2020. The line drops gradually over the years reaching about 30 % reduction of nitrogen use per year while the target was 10 % reduction. This shows a positive progress on reducing the environmental impact.

In summary, the use case has provided evidence of a positive impact of IoT use on sustainability performance. For validation field 1 a yield increase has been recorded while the nitrogen and herbicide use are reduced significantly.

Table 3
Baseline and Target KPIs in two fields of "Within-field management zoning" use case.

KPIs	Functional unit	Validation field 1		Validation field 2	
		Baseline	Target %	Baseline	Target %
Yield	kg harvested product/ha/year	55	2	50	2
Haulm killing herbicide use	kg a.i./ha	0.8	−30	0.6	−30
Herbicide use	kg a.i./ha	3.55	−15	1.55	−15
Number of sprays with fungicides		16	−10	16	−10
Fungicide use	kg a.i./ha	4.68	−10	4.68	−10
Herbicide + fungicide use	kg a.i./ha	9.03	−20	6.83	−20

UC2.2 Happy cow

Table 4 shows the KPIs, functional units, baseline and target values of the KPIs in the Happy Cow use case. Like the previous use case, this use case has validated the IoT product in two validation trials.

The baseline and target values for yield and calving interval are different in the two validation fields. This indicates that use case expected different outcomes in the two trials while applying the same IoT technology.

Along the years 2017 to 2020, the use case has recorded improvement in e.g., milk yield. Although the use case did not yet reach the targeted value of milk yield, it has booked progress compared to the baseline (3 % increase). In contrast, an enormous reduction is achieved in 'days treated with antibiotics due to illness'. In 2020, a reduction of 48 % was achieved in Validation 1, and 88 % reduction in Validation 2.

UC4.2: Chain-integrated greenhouse production

The KPIs of the "Chain-integrated greenhouse production" use case have been validated in two countries: The Netherlands and Spain. Table 5 shows the KPIs, functional units, baseline and target values as defined by the use case in two validation fields.

The results show slight differences in baseline and target values of the same IoT solution in different validation fields. The target values here are defined by the expectation of experts who considered other influential factors that can impact the effectiveness of the solution.

Table 6 shows the heatmap that was created based on the current values compared to baseline and target values. Red cells indicate that the recorded values were under the baseline values. For example, the pesticide use in Validation 1 in 2020 has increased by 1.8 %, while the target was to reduce the use by 5.3 %. Orange cells indicate that the current values did not reach the target values but exceeded the baseline values. Green cells show that the current values exceeded the target values. For example, pesticide use was reduced by 20.8 % in Validation 2 in 2020 while the target was a reduction by 5.3 %.

Table 6 shows that most of the current values exceeded the baseline values (orange) specifically in Validation 1, and most of the target values were achieved in Validation 2.

UC4.3 Added value weeding data

The KPIs of the "Added value weeding data" use case have been defined and monitored in one validation field on an organic farm in Austria. Table 7 shows the KPIs by functional units, baseline (absolute value) and target values (in percentages).

Typically, organic farming can benefit from IoT when it helps to detect plant diseases through early warnings. The farmer can then prevent the disease to spread to a larger area on the field timely. As Table 7 shows, the spatial accuracy of yield prediction due to the IoT solution in this use case is expected to be 60 %.

Due to extreme drought in the summer of 2018, the test farm could not harvest, and therefore the target value of yield increase was recorded only in 2019. Accordingly, despite a drop in 2018, the labour efficiency increased by 11 % and exceeded the target value (5 %) in 2019 (Fig. 6).

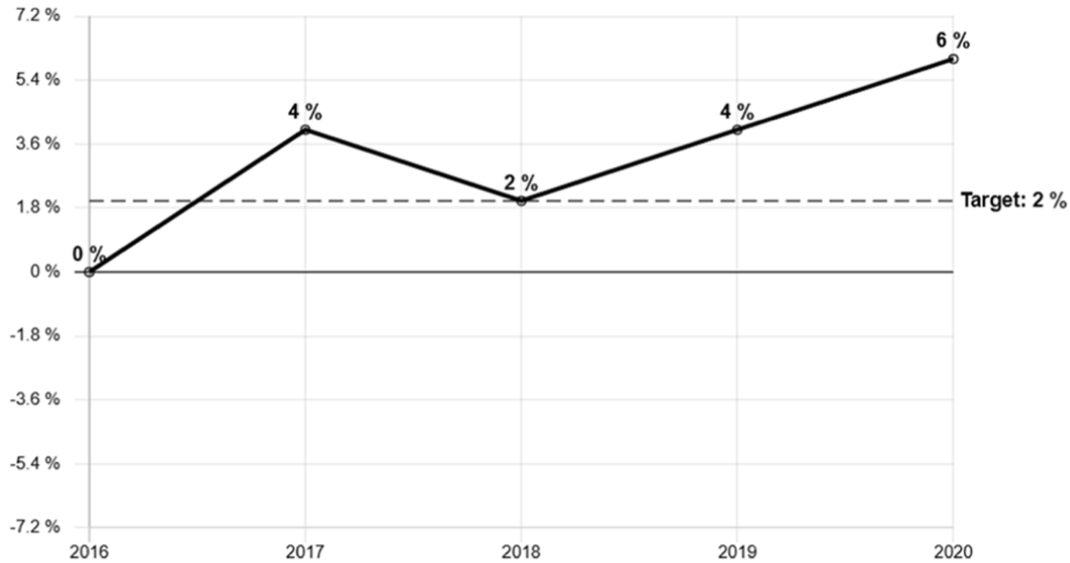

Fig. 3. Progress of yield increase of "Within-field management zoning" use case.

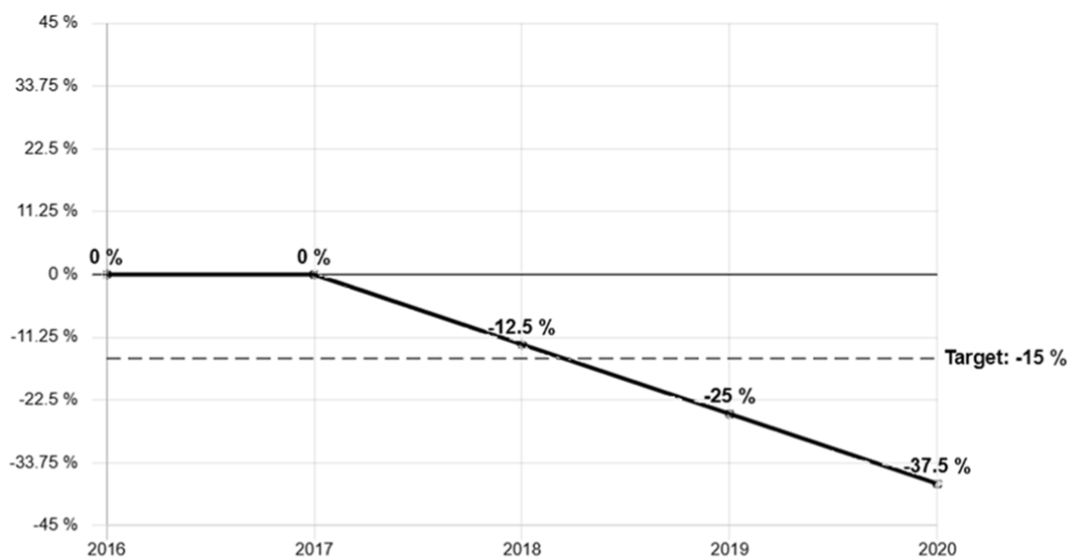

Fig. 4. Reduction of herbicide use of "Within-field management zoning" use case.

The labour efficiency was registered as machine and manual weeding operation. Due to highly changing conditions, it was not possible to use the machine in all situations. In some situations, the crop was already too big for a second weeding and then manual weeding was required which is more labour-intensive. As Fig. 6 shows, the use case could meet the target value.

UC5.1 pig farm management

The "Pig farm management" use case aimed at optimising pig production management by interoperable on-farm sensors and slaughterhouse data and was validated at 5 sites in two countries, Belgium and The Netherlands. Table 8 shows the KPIs by functional units, baseline and target values in five validation sites.

Table 8 shows that, although the baselines are different, the target percentages are in general the same, indicating that IoT solutions are relatively independent of external influences. Some baselines have been challenging to find due to the lack of historical datasets (e.g. reduced boar taint). In validation 1, no numbers of boars have been found in the dataset to use as a baseline, or the boar taint had not been registered by the slaughterhouses. Decreased health problems operationalised as number of treatments per animal per year has been used as proxy for animal welfare. An assumption here is that the less health problems, the less treatments will be used, eventually increasing animal welfare.

Fig. 7 shows the average daily weight gain of pigs in one of the validation farms of this use case recorded between 2016 and 2020. As illustrated, the average weight gain has exceeded the target value right from the beginning of the measurement (2017). It could mean that the target values for this IoT solution could have been set more ambitious afterwards.

In conclusion, the results show that often the baseline values are difficult, and sometimes even impossible to define due to the lack of available data. Sometimes the target values of the same solution vary in different geographical locations and seems to be dependent on the size and the type of farming (e.g. organic vs non-organic). Finally, the current measured values might indicate the impact of IoT on the sustainability performance. However, the external natural circumstances play a role too, and one needs to interpret the impact within a wider context.

Fig. 5. Reduction of Nitrogen use at the "Within-field management zoning" use case.

Table 4
Baseline and Target KPIs in two fields of "Happy Cow" use case.

KPIs	Functional unit	Validation 1 Baseline 2017	Validation 1 Target %	Validation 2 Baseline 2017	Validation 2 Target %
Milk yield	kg milk per lactation period of 305 days	9710	4	8303	6
Days treated with antibiotics due to illness	defined daily dose animal	1.82	−18	2.42	−18
Calving interval	days	400	−2.5	427	−9

4. Discussion

The main contribution of this paper lies in the developed set of instruments, practical tools to measure and monitor the contribution of IoT to sustainability in a real-life context. Based on the SDG framework, we developed a typology for measuring sustainability impact through key performance indicators. This typology has been applied to various agri-food sectors and can be used in the future by other, similar IoT cases. We expect that the typology can also be further enriched and improved.

The set of instruments provides a practical, stepwise approach on how to measure and monitor sustainability progress, and easily communicate and discuss the progress with relevant stakeholders. The application of the instruments in 5 case studies provides evidence for a positive contribution of IoT to a more sustainable agriculture. When using key performance indicators for monitoring, use cases sometimes found that current performance indicators outpace the target indicators when IoT was used. Exceeding target values can be considered as a great

Table 5
Baseline and Target KPIs in two fields of "Chain-integrated greenhouse production" use case.

KPIs	Functional unit	Test Farm 1 The Netherlands Baseline	Test Farm 1 The Netherlands Target %	Validation 2 Spain Baseline	Validation 2 Spain Target %
Productivity increase	kg crop harvested / m2 / year	15.00	7.7	12.55	7.7
Cost reduction	total variable costs (in €) on crop cultivation / m2 / year	4.50	−5.3	7.02	−5.3
Reduced pesticide use	costs pesticide uses on crop cultivation / m2 / year	2308.00	−5.3	7016.67	−5.3
Energy efficiency	KWH use on crop cultivation / m2 / year	1.54	−2.7	3.13	−3.4
Water contamination	kg nitrogen within the soil / ha	49.09	−5.3	533.09	−5.3
Water use	m3 water use on crop cultivation / m2 / year	33.30	−5.3	0.55	−5.3

Table 6
Heatmap of "Chain-integrated greenhouse production" use case.

KPI	Validation 1 The Netherlands 2018 (%)	Validation 1 The Netherlands 2019 (%)	Validation 1 The Netherlands 2020 (%)	Validation 1 The Netherlands Target (%)	Validation 2 Spain 2019 (%)	Validation 2 Spain 2020 (%)	Validation 2 Spain Target (%)
Productivity increase	0.4	4.7	−1.4	7.7	5.9	1.0	7.7
Cost reduction	0.0	−4.4	−7.1	−5.3	−10.8	9.5	−5.3
Reduced pesticide use	−0.3	−0.3	1.8	−5.3	−11.8	−20.8	−5.3
Energy efficiency	−2.6	−1.3	−0.7	−2.6	−7.8	−19.1	−2.8
Water contamination	−1.6	no data	−2.1	−5.3	−12.8	−11.3	−5.3
Water use	−0.2	0.0	−2.5	−5.3	−13.3	−10.3	−5.3

Table 7
Baseline and Target KPIs of “Added value weeding data” use case.

KPIs	Functional unit	Validation Austria	
		Baseline	Target (%)
Running hours	Machine running hours/ hectare per year (sugar beet)	2	−5
Running hours	Machine running hours/ hectare per year (pumpkin)	0.6	−5
Yield	Metric tonnes harvested product/ hectare per year (sugar beets)	32	5
Yield	Metric tonnes harvested product/ hectare per year (pumpkin)	0.4	5
Labour efficiency	Labour (fte) required for (sugar beets) weeding per hectare per year (weeder + manual, sugar beets)	80	5
Labour efficiency	Labour (fte) required for (pumpkin) weeding per hectare per year (weeder + manual, pumpkin)	3.6	5
Spatial accuracy of yield prediction	prediction error in days (lettuce). 4 weeks before harvest.	10	−60

performance. However, it can also be argued that the target indicators are not ambitious enough. Therefore, it is necessary to set target indicators flexible and as realistic as possible based on available reference values or best practices.

It should be emphasized that the data exhibited in this paper are based on self-reporting, which can be considered as a limitation. In some cases, it was difficult to control the measurement of the indicators because of practical limitations, such as budget. Ideally, machine-generated data should be trustful enough as a basis for measurements, without any human intervention, to avoid tempering with the data. However, in a progressive digital innovation adoption process, human interaction is often needed to correct and steer the technology operations, as well as the way data is generated and used. Blockchain technologies are considered as a possible solution to avoid data fraud (van Wassenaer et al., 2021). However, from a business perspective, application of such technologies should only be applied when sustainability impact is actually rewarded (e.g. by a premium price).

In some use cases, the challenge was to define the baseline, current and target values and collect appropriate data. Baseline values were not always available or were difficult to define due to two main reasons. First, some use cases had not yet identified their end-users at the beginning of the project, and therefore, they could not do the

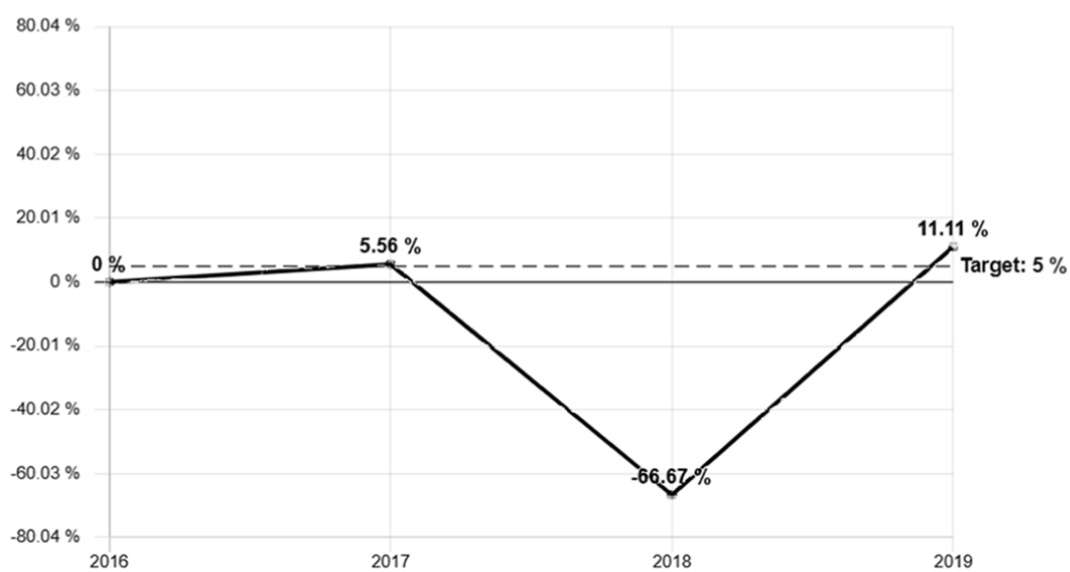

Fig. 6. Labour efficiency (FTE).

Table 8
Baseline and Target KPIs of “Pig farm management” use case.

KPIs	Functional units	Validation 1 (Belgium)		Validation 2 (Netherlands)		Validation 3		Validation 4		Validation 5	
		Base-line	Target (%)	Base-line	Target (%)	Base-line	Target (%)	Base-line	Target (%)	Base-line	Target (%)
Increase average daily weight gain	gram growth / delivered meat pig per day	642	8	830	6	816	6	860	6	848	6
Reduced pig mortality	% of animals lost in the fattening phase per year	8.6	−10	2.5	−10	2.1	−10	5.1	−10	6	−10
Reduced boar taint	% carcasses of a batch identified with boar taint	no boars in dataset	−20	not registered by slaughterhouse	−20	no data	−20	1.3	−20	2.7	−20
Animal Welfare Decreased health problems	Number of treatments per animal per year	1.38	−10	3.5	−10	1.4	−10	1.8	−10	0.2	−10
Improved feed conversion	kg feed per kg growth	2.42	−10	2.5	−10	2.44	−10	2.51	−10	2.54	−10

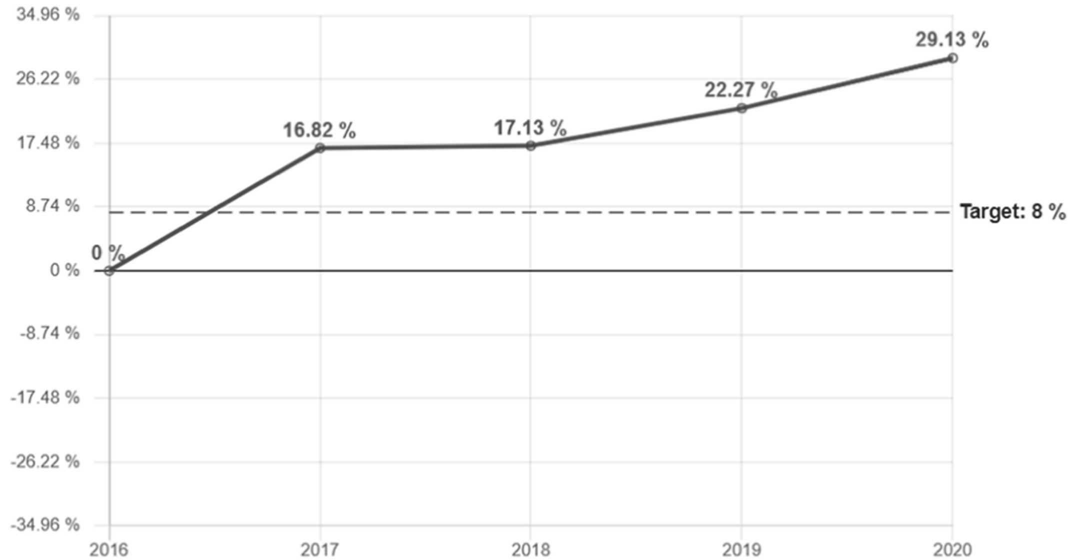

Fig. 7. Average daily weight gain.

measurements. Second, use cases had difficulties retrieving data from testbed farms due to the absence of historical data. Some use cases defined target values for certain KPIs after they ran several experiments with the IoT solutions. Other use cases changed the target values over time. This due to the fact that some use cases had to develop completely new KPIs which were difficult to monitor because the testbed farm did not possess the right data.

The approach and results of this paper can be useful for different stakeholder groups. Primarily, practitioners in similar projects can use it for managing and monitoring performance of IoT and explore how IoT contributes to sustainability goals. Secondly, the paper provides opportunities for policy makers and investors to evaluate how sustainability goals can be achieved by IoT, justifying public or private investments in these types of projects and innovations. Finally, academics can refer to the KPI framework that was developed and further investigate the relationship between sustainability and IoT.

The various use cases gave a good illustration of how IoT can be related to sustainability. The hypothesis that IoT contributes to sustainability performance was tested and evaluated in a real-life context providing practical evidence. It can be expected that this will help to upscale innovations like these because practitioners, e.g., farmers or advisors, are often more convinced by peers then outcomes of a laboratory experiment. In the current setup and approach, it is a challenge to provide scientific evidence because of other interacting factors and limited time series. Nevertheless, findings can be complemented and further substantiated by other, more experimental research set-ups. For example, in relation to UC1.1, there is already scientific evidence provided that the used methods significantly contribute to sustainability (Kempenaar et al., 2017).

It should also be emphasized that the use cases were embedded in a multidisciplinary, collaborative, agile approach embracing a demand-driven methodology. Although the focus was not particularly on sustainability, it had potential trade-offs with the business model, technical feasibility and user experience. The strength of the KPI approach is that it tries to reach sustainability-by-design, transforming sustainability into a business opportunity. A potential pitfall of this method is that the focus is on positive indicators. Negative indicators are mostly not considered because of business interests. Nevertheless, the approach as such allows negative impact (e.g., labour market, energy use) measurement in a project design once not only commercial interests, but also macro-economic and ecological interests are considered.

Finally, the IoF2020 project has also developed an IoT catalogue (IOT Catalogue, 2022) in which IoT solutions can be explored based on domain-related value propositions and/or ICT problems described in use-cases. Users can inspect solutions and technologies from other domains that might fit their intentions or analyse use cases that are similar to their projects to promote synergies and reusability between application domains.

5. Conclusions

This paper showed how digital technologies such as IoT can contribute to sustainability in agriculture. A typology and approach were introduced that supports especially practitioners to work on sustainability goals in a real-life context in a systematic, stepwise manner. Different use cases from various agricultural sectors illustrated how this approach can be applied to a wide range of sustainability goals. The results from the use cases generally showed that IoT can greatly improve sustainability although other factors, such as drought, can also significantly influence the outcome. When more use cases in the future use the typology and approach of this paper, we expect that further steps forward to sustainability goals can be made.

CRediT authorship contribution statement

Sjaak Wolfert: Writing – review & editing. **Gohar Isakhanyan:** Investigation, Conceptualization, Methodology.

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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Appendix 1. Detailed use case descriptions

This appendix describes the 5 selected IoT use cases in more technical detail also providing more details on the data that were measured.

UC1.1 Within Field Management Zoning

In Europe, arable farming faces increasing requirements and challenges when it comes to resource efficiency, environmental protection, transparency and chain optimization. Therefore, this use case aimed to support farmers to manage their farms more efficiently and achieve better interaction with their environment. The use case showed how data from different types of sensors (soil moisture, soil organic matter, climate, etc.) can be used to predict yields, define management zones and prepare task maps for farm equipment (e.g. variable application of herbicides, water and fertilizers). The use case also explored how data can be shared within chains to optimize efficiency. The challenges of UC 1.1 were to demonstrate 4 IoT applications in potato production and storage on two farms in The Netherlands and Belgium by:

1. Wireless connectivity between standalone sensors and the LoRa network - develop software or acquire generic enablers to visualize the sensor data of the different sensors in a way so that the data can be compared and use the data in management decisions and FMISs.
2. Biomass monitoring and yield prediction using satellite images, crop growth models and yield sensors on harvesters in potato - extra effort was needed to extend the yield/mass mapping system on the harvester to be able to make good quality net yield maps. On clay soil, this was hampered by presence of variable and too many cloths of soil in the data.
3. Use of VRA maps in potato crop management - the process of sending VRA maps to farm machines (planters, sprayers, spreaders) needed to be improved; too many software packages were involved. Also tools needed to be developed to retrieve as-applied maps from farm equipment into the FMIS. Variable yield expectation maps needed to be included into the fertilizer advisory DSS.
4. A tracking system of potatoes stored in bulk – needed to extend efforts to develop the track-and-trace-system for storage in the bulk storage facility and the potato quality sensor system (measuring dry matter content of tubers) needed to be added to the storage line.

The table below provides more details on the main data that were measured in this use case.

Data	Measurement Technique/ Dataset used	Deployment Site (s)	Crops used for task	Frequency of Data Collection/ Access	Associated data model/ format
Soil property data (org. matter, clay content, pH)	Soil sensor systems (Dualem and Veris)	1, 2	Potato	Once per year, winter before planting	ISOXML or Shape
Crop biomass data (NDVI, WDVI, CI, NDRE)	Optical sensor systems (remote and nearby)	1, 2	Potato	Several times per year	ISOXML or Shape
Climate data (temperature, RV, soil moisture)	Various systems	1, 2	Potato	Several times per year	ISOXML or Shape
Yield data	Grimme weight sensor	1, 2	Potato	Once per year, end of growth season	ISOXML

UC2.2 Happy Cow

The goal of this use case was to significantly increase the adoption of sensor technology within farm management to monitor cow behaviour to predict issues, give insights on heat detection and health, and recommend solutions to farmers. An Artificial Intelligence-based agent enabled to gather and interpret these data to really help farmers to improve dairy farming by understanding animal and herd characteristics if the information is delivered in a manner that is useful and fits to the farmer.

The key actors are conventional or organic dairy farmers, where the cows' movements are monitored with motion sensors. These sensor were attached to the neck of the cow (more comfortable position) during daily activity. Once back to the farm and during the night the data are transmitted through an high-efficient, long-range wireless communication network and sent to the data storage for interpretation and decision taking. The measured data from the network of distributed sensors (cow sensors) was collected through a wireless connectivity technology to allow daily monitoring of the cow parameters and simplify the adoption of this technology. Two different technologies for the wireless network were used offering a great flexibility in the way cows sensors and farm gateway can be connected. Both options relied on a Sub-1 GHz wireless communication network (LPWAN). The first option can be used in all cases where a local wireless gateway can be installed. In this case all cow sensor nodes can be interconnected using a mesh network approach based on the 6LowPAN communication protocol. All the data and relevant information transited through the local gateway to the cloud service. The second option was based on Sigfox technology and allows each and all of the sensor nodes to communicate the measured data directly to the Cloud service, without the need of a local gateway installation. Both proposed solutions made use of a single radio transceiver (S2-LP) featuring ultra-low-power and highly-efficient performances. Bluetooth Low Energy communication is offered through the BlueNRG Application Processor family. A dual-radio BLE and Sigfox sub-system was made available by the joint usage of BlueNRG Application Processor and S2-LP radio.

The table below provides more details on the main data that were measured in this use case.

Data	Measurement Technique/ Dataset used	Deployment Site (s)	Animals used for task	Frequency of Data Collection/ Access	Associated data model/ format
Milk yield	Current and historical milk recordings	1,2,3	50	Monthly	Kg / 305 day / cow in a SQL database table
Inseminations	Provided by the farmer	1,2,3	50	Monthly	Number of inseminations / lactation / cow in a SQL database table
Antibiotics treatments	Provided by the farmer	1,2,3	50	Monthly	Number of treatment days / cow in a SQL database table
Behaviour	Ida tag through AI	1,2,3	50	Real time	

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Data	Measurement Technique/ Dataset used	Deployment Site (s)	Animals used for task	Frequency of Data Collection/ Access	Associated data model/ format
					Proprietary models, output depends on the need
Diseases	Insights created by Ida	1,2,3	50	Real time	Proprietary models, output depends on the need

UC4.2 Chain-integrated greenhouse production

This use case was about the development of an IoT web-based traceability system and DSS in the greenhouse tomato production involving large amounts of data, physical and virtual sensors, models, and algorithms focusing on important aspects such as water and energy use efficiency, safety, transparency, for both conventional and organic supply chain traceability systems of tomato.

The IoT architecture was divided into two sectors: Farm and Cloud. The Farm was composed by the sensors (wireless or by cable), actuators, a Local Server Scada and mobile/pc/tablet which can be used by workers in the greenhouse to send information wirelessly. The Local Server Scada is composed by a device which receives the signal from the sensors and send them to the Data Storage. That information can be accessed locally by an IoT backend (dashboard). The Cloud had software based in OpenStack and FIWARE, which helped to provide a public and private cloud. It was also possible to access that information through a dashboard.

The main challenge was to integrate the IoT solution in the value chain of fresh greenhouse tomato crops to ensure vegetable quality and traceability from the beginning (greenhouse system) to the end-user, obtaining optimum ambient conditions during the whole chain, reducing inputs and increasing energy efficiency, avoiding/reducing the use of pesticides. The implementation of an integrated IoT solution for the tomato value chain required the integration of a lot of information that is generated along this chain that should be filtered and made visible to various end-users in a meaningful way.

The table below provides more details on the main data that were measured in this use case.

Data	Measurement Technique	Deployment Site (s)	Crops used for task	Frequency of Data Collection	Associated data model/format
External temperature	Sensor	site 1	Tomato	30 s	Air temperature (°C) – timestamp in every sample
External humidity	Sensor	site 1	Tomato	30 s	Air humidity (%) – timestamp in every sample
Wind speed	Sensor	site 1	Tomato	30 s	Wind speed (m/s) – timestamp in every sample
Wind direction	Sensor	site 1	Tomato	30 s	Wind direction (°) – timestamp in every sample
Raining detector	Sensor	site 1	Tomato	30 s	Raining presence (Yes/No) – timestamp in every sample
External CO_2	Sensor	site 1	Tomato	30 s	Air CO_2 (ppm) – timestamp in every sample
External CO_2	Sensor	site 1	Tomato	30 s	Air CO_2 (ppm) – timestamp in every sample
External Global Radiation	Sensor	site 1	Tomato	30 s	Radiation (W/m^{-2}) – timestamp in every sample
Active Power	Sensor	site 1	Tomato	30 s	Electrical consumption (W) – timestamp in every sample
Reactive Power	Sensor	site 1	Tomato	30 s	Electrical consumption (W) – timestamp in every sample
Electrical frequency	Sensor	site 1	Tomato	30 s	Electrical frequency (Hz) – timestamp in every sample
Inlet temperature for heating	Sensor	site 1	Tomato	30 s	Water temperature (°C) – timestamp in every sample
Outlet temperature for heating	Sensor	site 1	Tomato	30 s	Water temperature (°C) – timestamp in every sample
CO_2 tank temperature	Sensor	site 1	Tomato	30 s	CO_2 temperature (°C) – timestamp in every sample
Heating water temperature	Sensor	site 1	Tomato	30 s	Water temperature (°C) – timestamp in every sample
Dehumification grid temperature	Sensor	site 1	Tomato	30 s	Grid temperature (°C) – timestamp in every sample
Dehumification outlet temperature	Sensor	site 1	Tomato	30 s	Air temperature (°C) – timestamp in every sample
Dehumification inlet temperature	Sensor	site 1	Tomato	30 s	Air temperature (°C) – timestamp in every sample
Greenhouse temperature	Sensor	site 1, 3–8	Tomato	30 s	Air temperature (°C) – timestamp in every sample
Greenhouse humidity	Sensor	site 1, 3–8	Tomato	30 s	Air humidity (%) – timestamp in every sample
Greenhouse global radiation	Sensor	site 1, 3–8	Tomato	30 s	Radiation (W/m^{-2}) – timestamp in every sample
Greenhouse PAR radiation	Sensor	site 1	Tomato	30 s	PAR radiation (W/m^{-2}) – timestamp in every sample
Greenhouse CO_2	Sensor	site 1, 3–8	Tomato	30 s	Air CO_2 (ppm) – timestamp in every sample
Greenhouse PAR radiation	Sensor	site 1	Tomato	30 s	PAR radiation (W/m^{-2}) – timestamp in every sample
Greenhouse PAR radiation	Sensor	site 1	Tomato	30 s	PAR radiation (W/m^{-2}) – timestamp in every sample
Greenhouse soil temperature	Sensor	site 1	Tomato	30 s	Soil temperature (°C) – timestamp in every sample
Greenhouse Internal Radiation	Sensor	site 1	Tomato	30 s	Global radiation (W/m^{-2}) – timestamp in every sample
Aerothermal heater	SCADA	site 1	Tomato	30 s	Use of heating (on/off) – timestamp in every sample
Dehumidification	SCADA	site 1	Tomato	30 s	Use of dehumidification (on/off) – timestamp in every sample

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Data	Measurement Technique	Deployment Site (s)	Crops used for task	Frequency of Data Collection	Associated data model/format
Humidification	SCADA	site 1	Tomato	30 s	Use of humidification (on/off) – timestamp in every sample
Side ventilation	SCADA	site 1	Tomato	30 s	Use of side ventilation (on/off) – timestamp in every sample
Top ventilation	SCADA	site 1	Tomato	30 s	Use of top ventilation (on/off) – timestamp in every sample
Heating pump	SCADA	site 1	Tomato	30 s	Use of heating pump (on/off) – timestamp in every sample
LEDs Lamps	SCADA	site 1	Tomato	30 s	Use of LEDs lamps (on/off) – timestamp in every sample
Blower	SCADA	site 1	Tomato	30 s	Use of CO_2 blower (on/off) – timestamp in every sample
Irrigation pump	SCADA	site 1	Tomato	30 s	Use of irrigation pump (on/off) – timestamp in every sample
Irrigation valve	SCADA	site 1	Tomato	30 s	Use of irrigation valve (on/off) – timestamp in every sample
3 ways valve CO_2	SCADA	site 1	Tomato	30 s	Use of 3 ways valve (on/off) – timestamp in every sample
Leaf wetness	Sensor	site 1	Tomato	30 s	Water condensation on leaves (%) – timestamp in every sample
Leaf wetness	Sensor	site 1	Tomato	30 s	Water condensation on leaves (%) – timestamp in every sample
Substrate Water Content	Sensor	site 1	Tomato	30 s	Substrate water content (%) – timestamp in every sample
Substrate Water Content	Sensor	site 1	Tomato	30 s	Substrate water content (%) – timestamp in every sample
Corridor temperature	Sensor	site 1	Tomato	30 s	Air temperature (°C) – timestamp in every sample
Corridor humidity	Sensor	site 1	Tomato	30 s	Air humidity (%) – timestamp in every sample
CO2 Flow	Sensor	site 1	Tomato	30 s	CO_2 flow (ppm) – timestamp in every sample
Tube CO_2 concentration	Sensor	site 1	Tomato	30 s	Air CO_2 (ppm) – timestamp in every sample
Active Power heating	Sensor	site 1	Tomato	30 s	Electrical consumption (W) – timestamp in every sample
Outlet pressure	Sensor	site 1	Tomato	30 s	CO_2 tank pressure (Bar) – timestamp in every sample
Proportional valve	Sensor	site 1	Tomato	30 s	CO_2 valve opening (%) – timestamp in every sample
Inlet pressure	Sensor	site 1	Tomato	30 s	CO_2 tank pressure (Bar) – timestamp in every sample
Outlet pressure	Sensor	site 1	Tomato	30 s	Proportional valve pressure (Bar) – timestamp in every sample
inlet blower outlet	Sensor	site 1	Tomato	30 s	Proportional valve pressure (Bar) – timestamp in every sample
Outlet blower outlet	Sensor	site 1	Tomato	30 s	Blower pressure (Bar) – timestamp in every sample
Inlet temperature CO_2	Sensor	site 1	Tomato	30 s	CO_2 tank temperature (°C) – timestamp in every sample
Outlet temperature CO_2	Sensor	Deployment site 1	Tomato	30 s	CO_2 tank temperature (°C) – timestamp in every sample
Inlet temperature Blower	Sensor	Deployment site 1	Tomato	30 s	Blower temperature (°C) – timestamp in every sample
Outlet temperature Blower	Sensor	site 1	Tomato	30 s	Blower temperature (°C) – timestamp in every sample
Smokes temperature	Sensor	site 1	Tomato	30 s	Smokes temperature (°C) – timestamp in every sample
Pressure valve	SCADA	site 1	Tomato	30 s	CO_2 valve opening (°C) – timestamp in every sample
Proportional valve heating	SCADA	site 1	Tomato	30 s	Irrigation valve opening (°C) – timestamp in every sample
Side ventilation	Sensor	site 1	Tomato	30 s	Potentiometer (%) – timestamp in every sample
top ventilation	Sensor	site 1	Tomato	30 s	Potentiometer (%) – timestamp in every sample
Aerothermal heating setpoint	SCADA	site 1	Tomato	30 s	Aerothermal heating setpoint (°C) – timestamp in every sample
Ventilation setpoint	SCADA	site 1	Tomato	30 s	Ventilation setpoint (°C) – timestamp in every sample
Biomass heating setpoint	SCADA	site 1	Tomato	30 s	Tubes-based heating setpoint (°C) – timestamp in every sample
CO_2 enrichment setpoint	SCADA	site 1	Tomato	30 s	CO_2 enrichment setpoint (ppm) – timestamp in every sample
CO_2 storage setpoint	SCADA	site 1	Tomato	30 s	CO_2 storage setpoint (ppm) – timestamp in every sample
Radiation setpoint	SCADA	site 1	Tomato	30 s	LEDs lamps setpoint (ppm) – timestamp in every sample
Humidity (humidification) setpoint	SCADA	site 1	Tomato	30 s	Humidification setpoint (%) – timestamp in every sample
Humidity (dehumidification) setpoint	SCADA	site 1	Tomato	30 s	Dehumidification setpoint (%) – timestamp in every sample

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Data	Measurement Technique	Deployment Site (s)	Crops used for task	Frequency of Data Collection	Associated data model/format
Irrigation water	Sensor	site 1	Tomato	30 s	Irrigation setpoint (%) – timestamp in every sample
Plant hanging Weight	Sensor	site 1	Tomato	2 s	Plant weight (kg) - timestamp in every sample
Plant hanging Weight	Sensor	site 1	Tomato	2 s	Plant weight (kg) - timestamp in every sample
Plant hanging Weight	Sensor	site 1	Tomato	2 s	Plant weight (kg) - timestamp in every sample
Plant hanging Weight	Sensor	site 1	Tomato	2 s	Plant weight (kg) - timestamp in every sample
Bag hanging Weight	Sensor	site 1	Tomato	2 s	Soilless bag weight (kg) - timestamp in every sample
Bag hanging Weight	Sensor	site 1	Tomato	2 s	Soilless bag weight (kg) - timestamp in every sample
Greenhouse solar radiation	Sensor	site 1	Tomato	2 s	Solar radiation (W/m^{-2}) – timestamp in every sample
Substrate water content	Sensor	site 1	Tomato	2 s	Substrate water content (%) – timestamp in every sample
Substrate electrical conductivity	Sensor	site 1	Tomato	2 s	Substrate electrical conductivity (dS m^{-1}) – timestamp in every sample
Truck intrusion control	Sensor	site 2	Tomato	10 s	Light present sensor (on/off) – timestamp in every sample
Truck localization	GPRS	site 2	Tomato	10 s	Truck position (coordinates) – timestamp in every sample
Truck load temperature	Sensor	site 2	Tomato	10 s	Vegetables temperature (°C) – timestamp in every sample
Product inlet	ERP	site 9,10	Tomato	By events	Production weight (kg) - timestamp in every sample
Product Outlet	ERP	site 9,10	Tomato	By events	Product weight (kg) - timestamp in every sample
Production categorization	ERP	site 9,10	Tomato	By events	Vegetable categorization (category) - timestamp in every sample
Production estimation	ERP	site 9,10	Tomato	By events	Production estimation (kg) - timestamp in every sample
Quality Standards	ERP	site 9,10	Tomato	By events	Load Quality Standard (code) - timestamp in every sample
Pesticide limits	ERP	site 9,10	Tomato	By events	Pesticide limits (number) - timestamp in every sample
Products alarms	ERP	site 9,10	Tomato	By events	Load alarms (code) - timestamp in every sample
Active ingredients	Lab analysis	site 9,10	Tomato	By events	Active ingredients (number) - timestamp in every sample
Supermarket request	ERP	site 9,10	Tomato	By events	Supermarket request (code) - timestamp in every sample
Packing	ERP	site 9,10	Tomato	By events	Packing type (code) - timestamp in every sample
Handling conditions	ERP	site 9,10	Tomato	By events	Handling conditions (code) - timestamp in every sample

UC4.3 Added value weeding data

The goal of this use case was to use weeding data to improve management performance of the farmer and machine service provider, to add economic value for farmers, retail chains and manufacturers of weeding machines. The use case was directly connected to all up-to-date organic farmers that are using vision-guided weeding machines. It was applicable for crops such as: endive, haricot, (red) lettuce, brassica, celery, sugar beets, cluster onion and all their varieties. This use case utilized the machine vision data of automated intra row weeding machines for better control of farm operations, including crop growth monitoring and yield prediction.

The main components of the IoT system are the Steketee Weeder, Field, Tractor and Harvest machine. These components contain the elements that give information to the system. Besides the elements within the components, there are a few stand-alone elements, which are a source of information such as a soil sensor or a smartphone app. In the Steketee Weeder, images are processed to extract field information like crop size, growing stage and weed pressure. The field component contains all elements, which have direct influence on the total yield from the field. The weed and crop visioning data are used in the Weeder as inputs to determine where to actuate the weeding elements. When there is an optimum control of these elements this was expected to lead will to a higher yield with the same input material. In the Harvest machine a yield monitor was added to get feedback on the performance of the crop. The yield of the crop is the final result of all actions performed in the last year and years before. This information was used to predict the optimum harvesting date and the estimated coming yield. The Tractor component contains the GPS information which is used to process the information from the field in a spatial way. This provided the opportunity to perform site-specific measures on the field. All these elements led to two DSS's, one DSS for the machine settings for the Steketee Weeder and one DSS for field/crop management.

Technical challenges were about developing the following functions:

- Process camera images of the weeding machine, combined with GPS-location and timestamp
- Connect other handheld sensor devices to the management system (crop lab-tests, soil samples, human-eye measurements) through a handheld with GPS and time stamp
- Log settings from Steketee IC-weeding machines and store it in the cloud
- Stand-alone yield mapping IoT-device to measure the pumpkin harvest per m^2
- Yield mapping device that is based on an existing module such as YieldMaster (Precision Makers), Potato yield mapping (Soil Essentials) or a module from CNH.
- Harvest prediction tool based on a combination of images and additional data from other sources, like weather forecast.

The table below provides more details on the main data that were measured in this use case.

Data	Measurement Technique/ Dataset used	Deployment Site (s)	Crops used for task	Frequency of Data Collection	Associated data model/ format
Crop images	Cameras installed on the weeder	Austria / The Netherlands	Pumpkins, sugar beets and lettuce	Continuous during weeding	Image data in Labview Binary format + GPS coordinates in NMEA:GGA sentence
Machine settings	Software on weeder	Austria / The Netherlands	Pumpkins, sugar beets and lettuce	Once during weeding	Settings + GPS coordinates
Machine parameters	Sensors on weeder	Austria / The Netherlands	*n.a.*	Once during weeding	Parameters in xml format + GPS coordinates in NMEA:GGA sentence
Crop parameters	Processing software on the weeder	Austria / The Netherlands	Pumpkins, sugar beets and lettuce	Continuous during weeding	Esri Shapefile
Weather data	Weather station	The Netherlands	Lettuce	Each hour during the growing season	Plain text CSV

UC5.1 Pig Farm Management

This use case worked on combining data across the value chain in order to provide the pig farmers with crucial information to effectively steer their management to reduce boar taint, health problems and improve productivity. A lot of information is already available on commercial pig farms, but it is fragmented and distributed across different sensor systems or data sources. By bringing this data together and adding analytics, predictions, warnings and visualization to it, the data will become transformed into valuable information for the pig farmer. The use case worked with four practical farms and one experimental farm. At the experimental farm specific installations occurred in 2017 to be able to monitor pigs at an individual level. These installations include sensors for feeding patterns and consumption, drinking patterns and water consumption, weight gain, climate monitoring and RFID readers. Technical challenges were mainly related to making the hardware work in a pig barn and to the stability of the logging systems. At the practical farms, the existing infrastructure and hardware was used as much as possible. In 2018, the farms were connected to the IoT platform, cloud service and business intelligence dashboard through dedicated adapters. The same was done for the slaughterhouses. At the experimental farm, a new sensor was developed that can measure individual weight gain in the pens with regular feeding systems.

The table below provides more details on the main data that were measured in this use case.

Data	Measurement Technique/ Dataset used	Deployment Site (s)	Animals used for task	Frequency of Data Collection	Associated data model/ format
Carcass data	VION database	1–5 by site 6	All batches	At slaughter	Carcass parameters from VION database
Boar taint	Human sniffers	1–5 by site 6	All batches	At slaughter	Occurrence (%)
Transport & waiting times	Schedules	1–5 by site 6	All batches	At slaughter	Duration (hr)
Genetics & sow data	FMIS	Site 1–5	All batches	At insemination & birth	Boar and sow line, parity, # piglets
Pen and Barn characteristic	Site visit	Site 1–5	All batches	Once per barn	Size (m^2), ventilation type, flooring, etc.
Batch characteristics	Notes, site visit	Site 1–5	All batches	Once per batch	Pen, group size, composition, etc.
Health	Notes, treatments	Site 1–5	All batches	Daily	Treatments (#), problems (#)
Water Consumption	Sensor	Site 1–5	All batches	1x /hour	Water consumed (Litres)
Feed Consumption	Sensor	Site 1–5	All batches	1x /hour	Feed consumed (Kg)
Daily Growth	Sensor	Site 1–5	All batches	1 × / day	Weight measured (Kg)
Climate	Sensor	Site 1–5	All batches	1 × / day	Temp (°C), Humidity (RH)
Ind. feed consumption	Feeding station + RFID	Site 1	60 pigs *3 rounds	1 × / hour	Feed consumed (Kg),timestamps (start/end)
Ind. weight	Weighing scale + RFID	Site 1	120 pigs *3 rounds	1 × / day	Weight (Kg), timestamp
Ind. water intake	Flowmeter + RFID	Site 1	120 pigs *3 rounds	1 × / hour	Water consumed (Litres), timestamps (start/end)
Ind. feeding behaviour	RFID sensor	Site 1	120 pigs *3 rounds	1 × / hour	RFID readings
Ind. drinking behaviour	RFID sensor	Site 1	120 pigs *3 rounds	1 × / hour	RFID readings

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