Sustainable intensification of food production through resilient farming systems in West & North Africa

WP1

Deliverable D1.4

Smart farming and monitoring technology overview

Task leader: ATB

Involved partners: FL, LUKE, BOKU, ISEG

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ABSTRACT

SustInAfrica deliverable 1.4 represents the results of the joint efforts of FarmerLine, the Leibniz Institute for Agricultural Engineering and Bioeconomy (ATB), the University of Natural Resources and Life Sciences (BOKU) and the Natural Resources Institute Finland (LUKE). A database of recent research activities, technologies, businesses and scientific projects concerning the agricultural sector in Europe and the western world as well as initiatives working with African smallholder farmershas been created. This is now available for interested user groups and thus enhances the profile of sustainable intensification of smallholder farming structures in Africa. In addition, an evaluation of the database entries is included in this report, which also addresses the relevance of the respective development for smallholder structures in West and North Africa.

The scientific publications in this subject area were evaluated based on their findings in the areas of productivity (94 publications), profitability (84 publications) and ecosystem services (82 publications). An overview of the current scientific knowledge is given as short reviews on these topics in order to facilitate decision-making for the project partners in the implementation of smart farming and monitoring technologies.

The technological database (454 entries) were evaluated on the basis of 17 selected categories. Suitable developments were identified from the technological database and summarized in short reviews. To ensure that the interests of smallholders can be addressed comprehensively, the technological database is searchable and can thus contribute individually as a decision-making basis for an investment to promote sustainable intensification in agriculture. Relevant contact details for associated companies (311 entries) can be addressed by the database as well.

Existing projects and initiatives (30 entries) were also integrated in the database along with their approach to smart farming. The deliverable also links with the EU project Smart4All, which provides a database for partner technologies between European companies and partners from Eastern Europe and extends findings of the conducted research in the SustInAfrica Project.

All the database entries were integrated into the MergData platform and are openly available to interested stakeholders. All project partners are able to add further entries during the course of the project.

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1 Introduction

1.1 Objectives

In the SustInAfrica project, African smallholder farmers are supported with cutting edge scientific knowledge and modern technological developments. For this purpose, it is important to get an overview of current projects, companies, initiatives and research in the field of Smart Farming technologies. For this purpose, the deliverable conducted a literature and technology research and summarized the results in a database, which was made open available on the Mergdata platform from Farmerline.

1.2 Deliverable 1.4 and associated task 1.2a

This deliverable consists of a report of recent research activities, businesses, available technologies, research projects and initiatives regarding the agricultural technology sector. The report and database focus mainly on European developments in the smart farming sector, with relevance for smallholder farmers in Africa. The database collects research activities, businesses and technologies as well as projects and initiatives worldwide and is published via the Mergdata platform from Farmerline. The database gives a platform to search for suitable partners and applications in the area of smart farming and monitoring technologies for African smallholder farmers and associated agricultural service providers.

The deliverable D1.4 is partly described in subtask 1.2a of the SustInAfrica proposal, which reads as follows. “This task will gather information and knowledge on traditional, agro-ecological, and smart farming practices and monitoring technologies from literature (e.g. reviews and meta-analyses) and of selected communities in targeted AEZs […] and assess their efficiency on improving agricultural productivity while reducing environmental impacts of agricultural activities. Findings and criteria are defined by the needs of WPs 2 and 3 (e.g. history, present, future potential, transition). This task will conduct Literature review and/or meta-analysis to elucidate information about existing agricultural practices and smart farming and monitoring technologies, along their effects on productivity and delivery of ecosystem services. The literature review and/or meta-analysis will be done in accordance to gathered data and information collected from the ISI Web of Science, Scopus, data from Ministries in Charge of Agriculture in the 5 countries, and UN FAO database, etc. Screening of smart, open, and affordable monitoring technologies for farmers will be coordinated by ATB and Luke and conducted in collaboration with local experts mentioned in section B4 of this proposal for plant health (GH, NI, EG, TU), water, and soil management (GH, BF, NI, EG, TU). The screening will search for tools and solutions in previous and current research activities, businesses, research projects, and initiatives as well as already available technologies. A data base will be built and made available in FMP (www.mergdata.com). The database can be easily browsed from the web to provide a systematic summary of the findings with access to freely available tools and solutions. The database will be filtered to extract relevant future-oriented technologies that have potential to be tailored to the needs of smallholder farmers in Africa. Each sorted out technology will be ranked for their suitability of practical implementation for smallholder farming in African agriculture. The ranking will consider the current situation but also the future development in African agriculture.” (Source: Proposal SustInAfrica)

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1.4 Working steps of the deliverable and their responsibilities

For deliverable 1.4, the following working steps were defined as shown in Table 1.

Table 1. Tasks, milestones and teams involved

Subtask	From (month)	To (month)	Milestone	Teams involved
Database research	M01	M12	MS1; MS2	BOKU ATB
Database set up	M11	M12	MS2	Farmerline ATB
Enable online access to the database	M12	M14	MS2	Farmerline ATB
Select database entries relevant for SIA	M12	M13	MS2	ATB
Writing Report	M10	M14	MS2	ATB

1.5 Methodology for data collection

1.5.1 Research activities

In order to obtain an adequate overview of recent research activities, the ISI - Web of Knowledge database was systematically searched. To determine suitable search strings, a two-step approach was followed. First, main keywords were defined and then sub-keywords were collected through the existing expert knowledge. Second, the sub-keywords were further refined to the most important items in subsequent discussions between the project partners involved. The main keywords were also shortened in number to ensure a manageable search scope. As a result, three main keywords, “profitability”, “productivity” and "ecosystem services", were combined with 33 sub-keywords each. To filter all non-agricultural studies, the search string was adapted, excluding papers without the phrases ‘Agri*’, ‘Farm*’, ‘Horti*’, ‘Livestock’, ‘crop’, ‘field’ or ‘orchard’. In the end, the Web of Science Core collection was searched for publications according to 99 search strings, each with and without the keyword "small holder" (Annex 2 Findings for recent research activities in ISI Web of Knowledge all collections

Table 3). To provide a detailed overview of current research in smart farming, up to three papers from each of the 99 categories were analyzed. Preference was given to papers with the keyword "small holder". Reviews and recently published articles were also selected more frequently if they had a content overlap with the project.

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1.5.2 Available Technologies

A non-linear internet research was conducted to collect a summary of available smart farming and monitoring technologies. Technologies were found in diverse articles of non-scientific journals, in internet databases (e.g., SmartAkis) or directly on the companies' website. Found technologies were included into the database. Next to their name, the developing company, a use case category and a short explanation of the technology was given. Further information about prices and suitable farm sizes was given, when provided.

1.5.3 Businesses

Businesses, in the field of smart farming technologies, were delineated from the available technologies database branch. Information about address, websites and contact details of all listed companies and institutions were added.

1.5.4 Initiatives and projects

Initiatives and projects were added to the database from a basic internet research. Further entries were added as they were found searching for the technologies and when analyzing the recent research papers.

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2. Analysis of research activities

2.1 General database summary (Research activities)

The papers collected in the database for recent research activities provide a broad overview of the scientific publications of the last years. In agreement with our project partner, BOKU, we have chosen three specific topics relevant for smallholder farmers of the core communities in the SustInAfrica project, productivity (94 papers), profitability (84 papers) and ecosystem services (82 papers). Publications were chosen homogeneously from the 33 sub-categories as mentioned in 1.5.1 Research activities. Findings from these scientific publications are presented in the following sections.

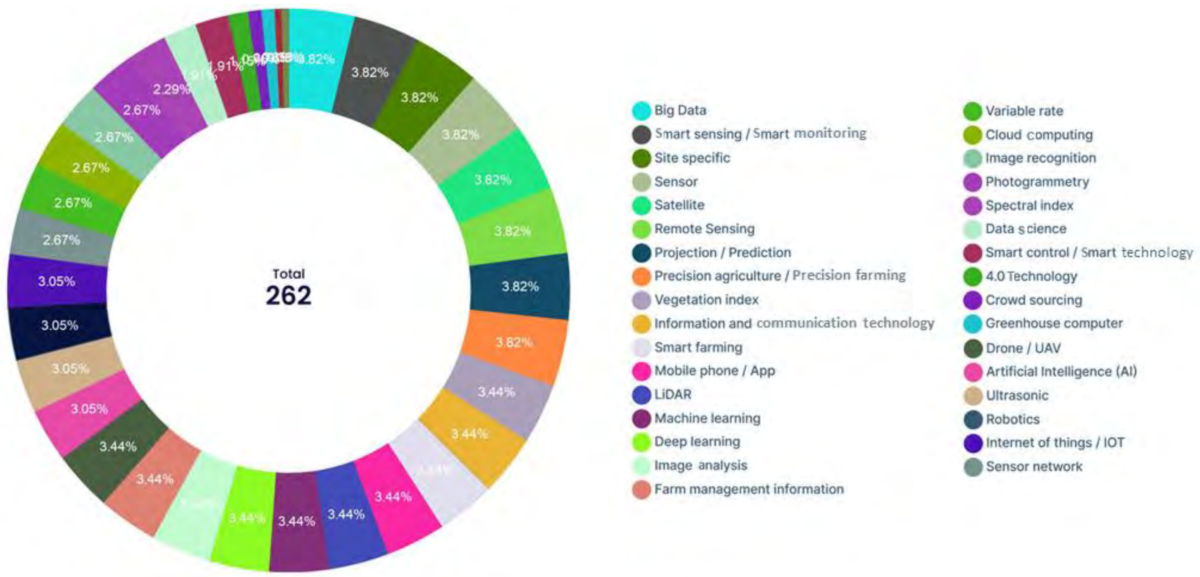

Figure 1Recent research publication findings homogeneously distributed over 33 sub categories

2.3 Findings for productivity

Productivity had the most search results in the literature research with 261396 entries (Table 4). Conducted research studies focused on the increase in crop yields (Loew 2018; Fabregas et al., 2019; Grieve et al., 2019; Santiteerakul et al., 2020; Kwesiga et al., 2020; Campolo et al., 2021) and biomass (Hämmerle, 2018; Mochida et al., 2020), animal husbandry (Bovo et al., 2020; Liseune et al., 2021) and also on agroecological practices, for a more diverse farm environment while aiming for a high productivity (Hoffmann et al., 2020). Especially in the context of decreasing arable land due to soil degradation or climate change in contrast to a currently increasing population, the necessity of a more productive land use was given.

Although it appears that larger farms have a positive impact on yields, at least as suggested by results for maize (Dutta et al., 2020), research studies were also looking for ways to increase the efficiency of food production for smallholder farmers. The proposed farming equipment for smallholder farmers was normally less expensive, easier to operate, and generally required less maintenance than equipment proposed for larger farms. The aim of most of the studies for smallholder farmers was to close the existing yield gap to the potential maximum yield (Hall et al., 2018; Dutta et al., 2020; Shah et al., 2021). Because smallholder farmers take a major role for food security in rural areas, supporting them to increase their productivity in a sustainable way was seen as important (Duncan et al., 2015).

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Productivity research for smallholder farmers in developing countries should further be adapted. Improvements should be aimed for small or even no investments (Onyango et al., 2021). It is interesting to exploit already existing technologies, e.g. mobile phones, that can be used to spread information for decision support. “The research to date on this topic is mixed, with studies finding both positive and neutral associations between phones and yields” (Quandt et al., 2020). Next to farming decisions, also the opportunity for networking with stakeholders and a better market access should be aimed for (Ogutu et al., 2014). In addition to the networks and services described above, smartphone and tablet applications were playing an increasingly important part (Matejcek et al., 2021).

One approach to increase productivity in agriculture that has been intensively researched in the last decade was precision agriculture, or smart farming. For farms in developed countries this involved using precise measurement sensors and sensor networks (Kumar et al., 2018; Mochida et al., 2019; Shafi et al., 2019; Gattani et al., 2019), complex evaluation algorithms (Elijah, 2018), adaptive machines (Sukkarieh, 2017; Zhao et al., 2020) as well as often trained artificial intelligence (Milosevic et al., 2019; Hesami et al., 2020; Sharma et al., 2021). Often, the main target was to respond to site-specific differences in the crop or individual animal parameters, for example, to improve crop protection or fertilization. Furthermore, timely responses to changes in the crop status were seen as important because agronomic traits, e.g. crop diseases, often remain undetected until they appear in later growth stages influencing e.g. the yield (Mochida et al., 2020). Extensive data collection and analysis has therefore become more and more a key element in modern agricultural systems (Shi et al., 2016; Saiz-Rubio et al., 2020). Aravind et al. (2017) wrote “smart farming and automated agricultural technology have emerged as promising methodologies for increasing the crop productivity without sacrificing produce quality. The emergence of various robotics technologies has facilitated the application of these techniques in agricultural processes. However, incorporating this technology in farms has proven to be challenging because of the large variations in shape, size, rate and type of growth, type of produce, and environmental requirements for different types of crops.” In that way, increased efficiency and decreased environmental risks can be achieved for agriculture reducing yield losses (Farooque et al., 2013; Saiz-Rubio et al., 2020; Li et al., 2020). The key to reach this goal would be the optimal distribution of inputs according to site-specific plant needs, such as water (Roy et al., 2021), fertilizers (Anjom et al., 2018; Schut and Giller, 2020) or plant protection agents (Agrimonti et al., 2021). The minimized operational costs would be another advantage of this technology (Delavarpour et al., 2021). The combination of data from different sources, such as soil and plant sensors in combination with satellite imagery, GIS and crop-soil simulation models were seen as promising for sub-Saharan smallholder farmers (Onyango et al., 2021). There were even big data applications for smallholder farmers in developing countries (Protopop and Shanoyan, 2016), but the use of this technology depends on investments. Lassoued et al. (2021) wrote “substantial physical investment, specialized human capital and effective data governance are critical to successful implementation of technological innovations associated with big data.”

In addition to the pure increase in productivity, many approaches focused on resource savings without the loss of crop yield or even while increasing yields at the same time (Sapkota et al., 2016; Balafoutis et al., 2017; Grieve et al., 2019; Esgario et al., 2020; Onyango et al., 2021). Here, the evaluation of data from a wide variety of sources was seen as crucial as well (Saiz-Rubio et al., 2020; Mann et al., 2011). Resources that should be optimized include seeds (Ogutu et al., 2014), fertilizers (Maresma et al., 2016; Vatsanidou et al., 2020), pesticides (Anifantis et al., 2019; Santiteerakul et al., 2020) or water (Ezenne

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et al., 2019; Hendawy et al., 2019; Nhamo et al., 2020; Li et al., 2020; Roy et al., 2021; Kamarudin et al., 2021). Agriculture shows a particularly high consumption of the latter resource. It accounts for nearly 70% of global freshwater consumption (Arenas et al., 2016). In order to counteract the influence of local water shortages due to climatic changes, it is therefore necessary to precisely adapt the water applied to the crop requirements (Arenas et al., 2016).

Another important topic for increasing the productivity was soil quality management. To achieve optimal soil conditions for plant growth, researchers investigated, e.g., optimal fertilization rates (Hoffmann et al., 2020; Schut and Giller, 2020), clay content for improving irrigation (Falco et al., 2021), the implementation of a universal soil quality index (Andrade et al., 2021) or the use of plant residues preventing erosion (Micheletto et al., 2020). The latter practice showed in the study a significant increase in maize yields as a suitable low-input strategy for smallholder farmers (Hoffmann et al., 2020). For a better estimation of site specific inputs it is necessary to sample the soil more intensively (Schut and Giller, 2020). However, laboratory soil analysis is expensive, so that most fields of smallholder farmers are insufficiently characterized regarding soil variablility (Campolo et al., 2021). The IsDAsoil map grants a 30 cm resolution map for soil properties for Africa (Hengl et al., 2020).

Diversifying crops is another way to achieve better soil conditions. Intercropped fields, such as maize combined with sown oats or cowpea, showed promising results in increasing soil organic carbon and yields after a few years (Hoffmann et al., 2020). ATB conducted an intercropping trial using maize and soy beans, for the later analysis in the SustInAfrica (SIA) project with unmanned aerial vehicle (UAV) imagery. Collected data show the two crops destinguishable in the multispectral images.

Stress factors in crops include diseases, pests, weed pressure, nutrition or water shortage which diminish yields or opens yield gaps. They should be prevented and action should be taken as early as possible (Grieve et al., 2019; Singh et al., 2020; Roper et al., 2021; Kamarudin et al., 2021; Ngugi et al., 2021; Rahman et al., 2021; Shah et al., 2021). Therefore a rapid assessment of the plant health status is needed. Modern methods for the assessment of stress factors in crops included the combination of classic sensors with smart platforms such as UAVs, for example to prevent drought (Park et al., 2017; Kamarudin et al., 2021), or smart phones (Ahmad et al., 2020). Also, the combination of image data with machine learning algorithms for weed, pest and disease detection (Esgario et al., 2020; Hasan et al., 2020; Singh et al., 2020; Shah et al., 2021) or plant omics analysis in phenotyping stress tolerance related genes (Mochida 2015) played an important role among the researched studies. The better potential to reveal stress situations in crops may also improve the resilience to climate change effects (Ferreira et al., 2021).

For applying inputs in a more timely and accurate manner, decision support systems may increase productivity and minimize resources use (Sukkarieh, 2017; Loew, 2018; Nhamo et al., 2020; Santiteerakul et al., 2020). Data for such systems can be provided from different sources and analyzed by specific algorithms (Li et al., 2020; Falco et al., 2021). It should be aimed to summarize the results in a simple management decision for the farmer. Similar systems exist for animal husbandry or fishing (Emmett et al., 2016).

For smart farming, advances in the analysis of complex and large data were linked with recent developments in artificial intelligence (AI) in order to target the increase in agricultural production. In developed countries, the last decade has seen an immense development in the communication of

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diverse sensors to sensor networks (Prodanović et al., 2020; Taheri et al., 2020) and the Internet of Things (IoT), so that sensor data can now be accessed and collected from anywhere on the globe (Li et al., 2020). This also increased the demand for powerful data processing tools. AI in agriculture has been already well investigated in large parts of the food production for this purpose. One expectation is that AI technologies may have positive effects on production by minimizing labor and resource use (Roy, 2021). Sharma et al. (2021) wrote "Machine learning together with Internet of Things enabled farm machinery are key components of the next agriculture revolution." The same authors explored the application of machine learning in precision agriculture for the prediction of soil parameters and crop yield, for disease and weed detection in crops and for assessing crop quality and yields. Further, they reviewed the use of machine learning in precision livestock production by predicting fertility patterns, diagnosing eating disorders and cattle behavior and also including intelligent irrigation and harvesting techniques. Hasan et al. (2020) and Shah et al. (2021) showed an increase in the accuracy of model predictions for plant identification with up to 95% accuracy, counting and disease detection in the field (also Ahmad 2020 up to 92% accuracy) by using large artificial neural network architectures (deep learning). In the future, many of these tasks may also be performed directly by robots in the field (Aravind et al., 2017; Sukkarieh, 2017), addressing labor shortages in agriculture in developed countries (Grieve et al., 2019). However, model accuracy was seen as highly dependent on the collected training data (Burke et al., 2021) and many AI models were overfitting in specific scenarios. The transferability should be improved for this kind of data-driven models (Ngugi et al., 2021). Another issue relates to data security, which has been rarely explored so far (Prodanović et al., 2020). In addition, the development of highly sophisticated technological systems has been mainly focused on developed countries (Onwude et al., 2016). Therefore, the adaptation of technology for developing countries in Africa is limited due to the lack of compatibility, availability of resources to facilitate the technology adoption, cost of technology, government policies and adequacy of the technology for addressing the needs of the population (Onwude et al., 2016).

In addition to the improvement of data analysis, there was also active research in the area of sensor platforms. In particular, the development of unmanned aerial vehicles (UAVs) has recently been strongly promoted for agricultural use. With their high mobility, ability to achieve good area coverage, highly accurate data acquisition, and low investment costs, UAVs were seen as a good choice as a sensing platform. There has also been specific development of camera technology for UAVs. In addition to simple RGB cameras (Hall et al., 2018; Rinnamang et al., 2020), thermal (Nhamo et al., 2020) and multispectral cameras (Nhamo et al., 2020) are available for UAV use today. These specific cameras can be used to record plant geometries as well as crop health conditions (Farrell et al., 2018; Willcox et al., 2018) or crop performance estimates (Nuijten et al., 2019; Nhamo et al., 2020), among others. Ezenne et al. (2019) found UAVs equipped with thermal cameras most suitable for detecting crop water status improving real-time irrigation scheduling.

The low acquisition cost, small size, and high mobility of UAVs make them also suitable for being used by smallholder farmers in developing countries (Rahman et al., 2021). Nhamo et al. (2020) wrote "the technology improves smallholder agriculture by facilitating access to information on crop biophysical parameters in near real-time for improved preparedness and operational decision-making." For example, in Ghana a maize crop classification model was created from UAV imagery based on RGB data, allowing the vegetation percentage to be determined, which aids in crop estimation (Hall et al., 2018).

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Remote sensing with satellite platforms can deliver an even larger area coverage than UAV and the evaluation over longer time spans, with relatively little effort and input from the user. Satellite remote sensing helps to estimate crop yield (Burke and Lobell, 2017; He et al., 2018; Loew 2018; Wagner et al., 2020), carbon exchange (Jiang et al., 2021) or predictions for political decisions concerning agricultural resilience and food security (He et al., 2018). However, satellite imagery is often too coarse for smallholder land analysis, as the field sizes are often smaller than the resolution of the imagery (Jain et al., 2013). Nevertheless, active research has been conducted in the field. To some extent, information concerning Indian smallholders has already been extracted from Landsat imagery. The authors are confident that their method can be applied to other parts of the world as long as the same data basis is available (Jain et al., 2013). Also, satellite imagery data should be more supported with ground measurements to enable site-specific management (Burke and Lobell, 2017; Lobell 2020; Onyango et al., 2021). In Nepal, wheat productivity was increased by optimizing soil and fertilizer inputs (Campolo et al., 2021). However, especially in Sub-Saharan Africa, satellite imagery can be difficult to analyze because of small field sizes of the smallholder farmers, multi-cropping, and different crop species with similar phenologies. In tropical areas cloudiness during the growing season limits the view to the bottom of the atmosphere and thus the availability of sufficient data from space.

Nowadays, even common technologic consumer goods offer the possibility to contribute to an increase in agricultural production. For example, smart phones include different sensors that may help in agricultural management. Therefore, more and more projects use such portable devices to improve agricultural productivity (Matejcek et al., 2021). For example, these devices were used for positioning (Fabregas et al., 2019), detecting diseases (Ahmad et al., 2020) or determining specific growth stages (Hufkens et al., 2019). In addition to mobile phones as sensor platforms, they can also be used as communication devices to crowd source or exchange information and to establish communication networks. Even outdated mobile phones might be useful for these technologies, which may significantly increase the user base. Quandt (2020) determined a slightly positive correlation between telephone use for agricultural purposes and increased yields for smallholders. The forwarding of short message services (SMS) to interested parties is a cheap and a more readily available form of information transfer in Sub-Saharan Africa. 'Wefarm' in Kenya is one such technology, a SMS-based knowledge-sharing platform that enables farmers to connect with their peers and exchange knowledge about their production systems (Omulo and Kumeh, 2020).

In addition to the development and dissemination of modern technologies and approaches in agriculture, the adoption rate of farmers was also seen as crucial for increasing agricultural production. Especially if there is an information gap regarding the technology to the disadvantage of smallholders, agricultural adaptation was hindered (Ogutu et al., 2014). Moreover, technologies that have been developed for industrialized countries, and have led to increased production there, cannot always be easily transferred to smallholder systems in developing countries with the same effects (Aravind et al., 2017). Onwude (2016) wrote "The application of these technologies in some developing countries in Africa and Asia is limited by factors such as technology compatibility with the environment, availability of resources to facilitate the technology adoption, cost of technology purchase, government policies, adequacy of technology and appropriateness in addressing the needs of the population." To increase the adoption rate of proposed technologies, the perspective of achieving personal livelihood goals might be another motivator (Omulo and Kumeh, 2020). Specific training about the target technologies also led to increased adoption rates in addition to production increases (Fabregas et al., 2019).

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Additionally, the clear communication of risks increases confidence for adopting the technology (Oyinbo et al., 2019). In order to make appropriate political decisions for a better dissemination of new technologies, a precise understanding of the doubts and needs of the local farmers was required (Taheri et al., 2020). One of the biggest motivators to adopt new technologies is the added benefit that comes from the investments made. With investments as small as the cost of SMS services or smartphone purchases, the returns on investment can be easily achieved (Fabregas et al., 2019).

In the future, farmers may also need to adapt to new local conditions due to climate change. Protecting farmland against destructive weather events or a better resilience against temperature warming is critical to secure future yields (Jain et al., 2013; Rao 2018; Olawuyi and Mushunje, 2020; Agrimonti et al., 2021; Ferreira et al., 2021; Matejcek et al., 2021). Sultan wrote in 2016 "West Africa is known to be particularly vulnerable to climate change due to high climate variability, high reliance on rain-fed agriculture, and limited economic and institutional capacity to respond to climate variability and change." To secure future yields, smallholder farmers in the core communities in the SIA project will likely need to adapt. Better access to weather forecasts and climate data can be helpful in this regard (Mondal et al., 2015). The lack of infrastructures, such as electricity or network connections in rural areas, also limits the adoption of new technologies in the agricultural sector (Li et al., 2020). This is especially true for approaches that use local technology such as smartphones, wireless sensor networks or site-specific application technology. Satellite remote sensing, for example, is possible regardless of local infrastructure development and is therefore well suited for more remote regions (Jain et al., 2013).

2.4 Findings for profitability

Profits from agricultural production are a necessity for the livelihood of the farmers and secures their prosperity as well as that of their families. Increasing profits can provide incentives for the adoption of new technologies. Therefore, considering the economic benefits of introducing technological innovations is always of interest if widespread adoption should be targeted. Profits can be improved by reducing investments, increasing crop yields or minimize transaction costs between various stakeholders along the food chain (Bergvinson, 2017). The development of new market opportunities through improved quality of the product can also increase the profitability in agriculture. Nowadays, digital agriculture is helping smallholder farmers to realize economic potentials while saving resources and accelerating equitable economic growth in rural communities (Bergvinson, 2017).

Saving on the input of raw materials plays an important role in the profitability of an agricultural business. In order to avoid agricultural production costs exceeding the revenues (Capmourteres et al., 2018), reduction of the necessary costs until harvest has been a highly researched field. The relatively new technology of smart farming tries to achieve input savings while increasing yields. To achieve this, inputs to the system should be adapted to small-scale differences and thus optimally distributed in spatial and temporal terms. This improves profitability and production efficiency, and minimizes harmful environmental impacts (Koutsos and Menexes, 2019; Messina et al., 2020). For large farms in developed countries, this was achieved with advanced sensors, robotics and information and communication technology (Inoue, 2020). To save water, maps highlighting water requirement were generated by using weather, soil, and crop condition data (Borrero and Zablo, 2020; García et al., 2020). Fertilizers (Fitzgerald et al., 2010; Colaco and Bramley, 2018; Bazame et al., 2020; Laekemariam et al., 2020; McDaniel et al., 2020; Zhang and Li, 2021) and plant protection inputs (Trivedi and Ahuja,

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2011; Beckie et al., 2019) were optimally matched to expected harvests and profits (Silva et al., 2021). Specific tools for production efficiency analysis in smart farming such as data envelopment analysis and stochastic frontier analysis allowed researchers to see how efficient the outputs are generated were, regardless of the units of measurement of the inputs (Perez-Pons et al., 2021). Furthermore, the adoption rate for site-specific technologies can be reduced when systems fail to achieve higher profitability for the farmers. Here, machine learning algorithms may help to optimize site-specific technologies and raising profits (Saikai et al., 2020). Personal advisory extension services via digital technologies proved to increase profitability among smallholder farmers in Sub-Saharan Africa (Arouna et al., 2021).

Increasing yields also leads to profit increases, e.g., by providing better environmental conditions during the growing season or the use of monitoring technologies. Studies showed increased profitability by improving site conditions such as soil or relief conditions (Jokela and Nair, 2016; Bijarniya et al., 2020; Quiros-Vargas et al., 2020), detecting diseases in time (Roth et al., 2019; Hao et al., 2020; Afzaal et al., 2021), and optimizing fertilizer applications (Brinkhoff et al., 2019; Wang et al., 2019; Guerrero et al., 2021). For smallholder farmers in Rwanda, models showed that yield gaps for wheat could be minimized through denser seeding and higher nitrogen applications (Baudrona et al., 2019). Profitable cultivation in irrigated rice fields in Benin was demonstrated and profitability was positively correlated with education, access to credit, extension services, soil quality, amount of fertilizer and herbicide applied, and ownership of mobile phones (Nonvide, 2019). Optimizations for better profits were also made in orchards using monitoring strategies for fruit quality. Diseases on fruit trees or palms were detected (Malinee et al., 2021) and the degree of fruit ripeness (Faisal et al., 2020) or fruit quality (Sinambela et al., 2020; Zhena et al., 2020) for dates or palm fruit were determined. Sorting fruit by quality using spectrometric classification may also offer profit increase for apples or cherry crops (Mendoza et al., 2014; Shao et al., 2019). Research studies were also focused on the adaptation of fertilizer or pesticide application to tree structure in lemon or apple orchards (Zaman et al., 2005; Tona et al., 2018). Other studies investigated profit increases in animal husbandry (Rathod and Dixit, 2020) and in grassland management (Gebremedhin et al., 2019; Jayasinghe et al., 2019; Gargiulo et al., 2020; Legg and Bradley, 2020; Nguyen et al., 2021; Rosa et al., 2021).

Many of the applications mentioned above make use of remote sensing technologies. They provide a comprehensive database for quickly assessing optimization potentials over large areas and support site-specific management decisions (Khanal et al., 2020). Satellite remote sensing offers the opportunity of low-cost assessment of large agricultural areas. For example, it helps to identify cultivated or non-cultivated lands (Janus and Bozek, 2018), enables mid-season yield estimations (Filippi et al., 2020) or assessing plant health conditions by determining the normalized difference vegetation index (Caiserman et al., 2019; Stepanov et al., 2020). Combined with soil and environmental data, satellite imagery was also an important data input for establishing the ISDA soil map (Hengl et al., 2020). Unlike satellite platforms, UAV-based imagery offers very high spatial resolution and thus provides important insights into seasonal plant and soil differences (Moran et al., 1997) revealing even subtle differences in the canopy (Messina et al., 2020). UAVs were beneficial for agricultural optimization of profit, sustainability and environmental protection (Sinha, 2020). They were used to detect plant stress (Spachos and Gregori, 2019; Skevas and Kalaitzandona, 2020) or diseases (Garza et al., 2020) in time and to estimate crop yields early (Ballesteros et al., 2018). In addition to pure data

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collection, UAVs can also be used directly for agricultural applications. These include, for example, the application of seeds, pesticides or fertilizers, thus contributing to increased profitability (Inoue, 2020).

Farmers usually do not focus on the data but rather on the specific application in the field and thus possible increases in profit. Farm management information systems (FMIS) can be fed from various data sources, including not only current data but also previous records of site conditions, and thus support correct and timely decisions over the season. In this way, the production and profitability of a farm can be increased (Gsangaya et al., 2020; Li et al., 2020). According to Fountas et al. (2015), the purpose of FMIS today is "to meet the increased demands to reduce production costs, comply with agricultural standards, and maintain high product quality and safety." However, farmers may be reluctant to use FMIS because collecting, aggregating, and importing data into FMIS can be time consuming (Paraforos et al., 2017). To reduce this effort, IoT may automate the process of data collection and provision. Together with sensor technologies, Big Data and cloud computing, there is the opportunity, according to Himesh et al. (2018), "to move to the next level of farm productivity and profitability." Even more sophisticated, robotic technologies would make intelligent decisions directly, allowing for immediate and site-specific implementation in the future (Blanes et al., 2011; Farooque et al., 2013). These systems, characterized by high investment costs, will be an interesting solution to labor shortages in agriculture in the developed countries for large-scale farms (Vasconez et al., 2019), but will play a minor role for smallholder structures. Furthermore, the logistics of selling agricultural products can also be supported with IoT (Sun et al., 2020) or blockchain technologies (Chen et al., 2021). For controlled environments such as greenhouses, management support from trained artificial intelligences has already been shown to lead to a better performance than purely human-managed greenhouses (Hemming et al., 2020). Intensive research is currently underway to develop this type of assistance also for arable farming.

To increase adoption rates of new developed technologies, training plays an important role. Important motivators are technologies that are proven to increase profit or minimize risk of losses (Kuwornu et al., 2018; Monjardino et al., 2020). Mobile phone information networks can directly bring profit improvement when farmers get better prices selling their goods because of reduced information disadvantages (Arinloye et al., 2013) or indirectly act as information support in implementing new technologies (Cole and Fernando, 2021). For modern smartphones, smart farming app technologies in Sub Saharan Africa could already lead to 10% increases in rice farming profits (Arouna et al., 2021). However, according to Koutsos and Menexes (2019), if more advanced precision technologies are to be adopted in the manner of Western agriculture, "additional application or management costs and investment on new equipment and trained employees" are required, which can lower adoption rates.

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2.2 Findings for ecosystem services

The study of ecosystem services in their benefits and maintenance is an interdisciplinary task at different scales. It requires diverse agricultural actors to achieve an optimization of ecosystem services (Tixier et al., 2013). They certainly represent an essential variable in achieving food security and nutrition (Vurro et al., 2019). In addition to direct influences on diet through fishing (Emmett et al., 2016; Romano et al., 2018), hunting, and gathering edible plants, ecosystem services also influence environmental variables affecting crops, such as soil carbon content or water retention capacity (Forsmoo et al., 2018). To maintain ecosystem services the diversity of agricultural landscapes is important (Weigel et al., 2018). There is a bilateral influence factor between ecosystem services and food production. Consequently, the increasing mechanization of agriculture also leads to an influence of these devices on the ecosystems linked to them (Lajoie-O'Malley et al., 2020). While this mechanization process has led to an increase in crop yields on the one hand, it also threatens ecological efficiency and nutrient content on the other (Biradar et al., 2019).

Ecosystem services depend on local ecosystem structures. Therefore, the composition of local agricultural cultivation is an important factor influencing these. Agroforestry is recognized by the Intergovernmental Panel on Climate Change (IPCC) report in its simultaneous role in food security and its protection against land degradation and positive influence on carbon storage. In addition, this form of agriculture offers climate adaptation benefits and is therefore promoted as climate smart agriculture for smallholder farmers (Kearney et al., 2017). To increase the adoption of agroforestry, research is being conducted on the optimized implementation for smallholder farmers (Cisse et al., 2018) and the effectiveness of the system (Wolf et al., 2019). Precision agriculture is another very common practice especially on large scale farms in developed countries, which has also impacts on ecosystem services. Because of the potential environmental benefits, optimized rates of application could also be found among smallholder farmers in developing countries (Finge et al., 2019). Precision agriculture avoids the excessive use of resources and waste, thus causing less environmental pollution (Finge et al., 2019; Semeraro et al., 2019). Research is conducted on each input resource individually, e.g., for water, to understand ecosystem-resource interactions or to identify and quantify relevant ecosystem services (Shah et al., 2021). Further, there is regenerative agriculture, which according to Gosnell et al. (2019) "concerns itself with enhancing and restoring resilient systems supported by functional ecosystem processes and healthy, organic soils capable of producing a full suite of ecosystem services, among them soil carbon sequestration and improved soil water retention." Conservative agriculture is primarily intended to mitigate climate change and prevent the loss of agricultural land, e.g. through soil degradation. Increased emphasis is placed on the type of tillage and associated ecosystem services. For arid regions, modeled yield increases could be generated with this method if appropriate agricultural management decisions were assumed (Su et al., 2021). Real yield increases in maize could also be achieved for African smallholder farmers (Mubiru et al., 2017). Furthermore there is sustainable agriculture, which according to Corato (2020) "utilizes natural renewable resources in the best way due to their intrinsic features by minimizing harmful impact on the agroecosystems." Less holistic studies further address crop diversification for pest control (Bajwa et al., 2019; Hoffmann et al., 2020; Colbach et al., 2021), the status of insect pollinators (Willcox et al., 2018) or the harmful impact of invasive species (Dash et al., 2019; Rai and Singh, 2020).

To meet the need for sustainable intensification of agriculture, soil management that involves carbon sequestration, water purification and retention, nutrient and material cycles and biodiversity, in

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addition to soil productivity is needed (Techen and Helming, 2017). However, to achieve sustainable development goals, such as ensuring food security, soil must always be considered in the context of its associated ecosystem services (Bouma, 2014). For example, soil microorganisms (Steffi and Josephine, 2013) or soil pore characteristics (Cercioglu et al., 2018) as key factors for the soil fertility, the promoted plant health or delivered ecosystem services are investigated. There are also studies in the field of smart farming mainly focused on developed countries, e.g. Germany, that develop robotic, internet and communication technologies for optimizing soil management (Techen and Helming, 2017). In this context, also web-based platforms for orchards (Pandey and Tarun, 2019) or deep learning models for soil property estimation in an agricultural landscape (Jeong, 2020) have been developed for site-specific management. Farmers, who show a growing awareness of the importance of soils for crop production and the provision of ecosystem services (Rose et al., 2016), can further choose their crops to aim for reduced soil erosion, reduced pesticide and fertilizer impairment, or improved ecosystem services (Gu and Wylie, 2017).

The resilience of agricultural production and improvement of its impact on climate change is a field of intense scientific study today. Feeding the global population sustainably, nutritiously, equitably, and ethically in times of climate change is seen as a major challenge (Sapkota et al., 2016; Khanna et al., 2018; Stringer et al., 2020; Weiss et al., 2020). Particularly in areas where agricultural production is low and opportunities for adaptation to climate change are limited, there is a risk that productivity will continue to decline due to projected climate change (Manei et al., 2016). For example, increased drought events were diminishing provisional ecosystem services in Botswana by triggering land-use changes (Mugari et al., 2020). For estimating dynamic drought events and its impacts, the distribution of weather stations was too sparse and Mugari et al. (2020) argued that the vegetation indices from remote sensing data would be a viable alternative to assess the spatial dynamics of droughts in data-poor regions such as Bobirwa sub-district. Strategies to improve resilience to climate change include crop breeding for high yields and improved adaptive capacities to climatic changes (Harfouche et al., 2019) or using abandoned land for carbon storage (Bell et al., 2020).

Land use decisions in small-scale structures represent an important influence on local ecosystem services. Land use and land use change models are needed to better assess the impacts of these complex options (Celio et al., 2019; Ongsomwang et al., 2019). These are also used to assess the impacts of current agriculture on ecosystem services, agricultural and ecosystem productivity, carbon storage capacity, and the hydrological cycle (Bayer et al., 2021; Srichaichana et al., 2019). Nowadays, the development of ecosystem services and its interactions with the agricultural environment is predominantly monitored on a large scale by analyzing satellite image data (Emmett et al., 2016; Weiss et al., 2020). This includes crop distribution (Liang et al., 2019), soil properties (Maltese and Neale, 2018; Cucchiaro et al., 2020), crop production (Rosa et al., 2017; Hunt et al., 2019) as well as mapping of biodiversity or ecosystem services (Dronova et al., 2011; Pettorelli et al., 2014; Petrou et al., 2015; Martinez et al., 2016; Sinare et al., 2016; Rosa et al., 2017; Jones et al., 2018) or the evaluation of those maps as tools for decision makers (Ochoa and Urbina-Cardona, 2014). Further greenhouse gas emission calculations for farmland and livestock (Parente et al., 2019), leaf area index estimations (Kamal et al., 2016), plant health (Toukem et al., 2020) or biomass estimations (Kearney et al., 2017) are supported with satellite imagery. For African wetlands, satellite imagery is used to distinguish between different habitat types as well (Jacob et al., 2014). High-resolution data from UAVs provides a good area performance, while maintaining low investment costs. With UAV imagery it is possible to

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get insights to surface height models (Forsmoo et al., 2018), species richness for beetles (Woodcock et al., 2010), floral resources and pollinator populations (Xavier et al., 2018) or biodiversity estimations (Libran-Embid et al., 2020). UAVs can also provide plant structural parameters (Price et al., 2020) or reference data for plant abundance in large areas (Sankey et al., 2019). For smallholder farmers low-cost variations of UAV applications were successfully tested for tree biomass assessment in monoculture plantation (Miller et al., 2017) or yield prediction in agroforestry (Leroux et al., 2020).

Improving the quality of life for smallholder farmers from developing countries is also a challenge in rapidly changing rural economies (Adams et al., 2019). Smallholder farmers were found to be vulnerable to climate change, as they are particularly dependent on agricultural production or ecosystem services (Hannah et al., 2017). However, especially in remote, poverty-stricken areas, data to validate large-scale ecosystem service models is scarce (Sinare et al., 2016). In Africa, studies concerning the possibility of biofuel production and associated improvements in climate regulating ecosystem services for smallholder farmers have been explored (Romeu-Dalmau et al., 2018). In addition, farmers' existing knowledge of ecosystem services, such as the presence of natural predators of crop pests, or alternative defenses through pest management (Mkenda et al., 2020), and the prevalence and use of cell phones for agricultural information gathering have been studied (Baird and Hartter, 2017). Further scientific research has taken place on soil degradation. The associated losses in ecosystem services and biodiversity have negative effects on the agricultural supply of Africa's smallholder farmers (Mubiru et al., 2017).

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3. Available Technologies

3.1 General database summary (Technologies)

The database for technology research contains 454 entries. All listed technologies achieved TRL 9 standard. In addition to the name of the technology, the developer and country of origin, an assignment to a category as well as a description was given. The category was set either from the source if available or adapted by expert knowledge. Where available, an estimate of the field size for which the technology is viable was also provided. Furthermore, links to further information about each technology have been added to give interested users an entry for their research.

The collected results are publicly available on the MergData platform from Farmerline and can be viewed and searched in the technology section of the database query. In order to provide each user with clear options for narrowing down the search results, multiple search filters can be set. An example is given in Figure 2.

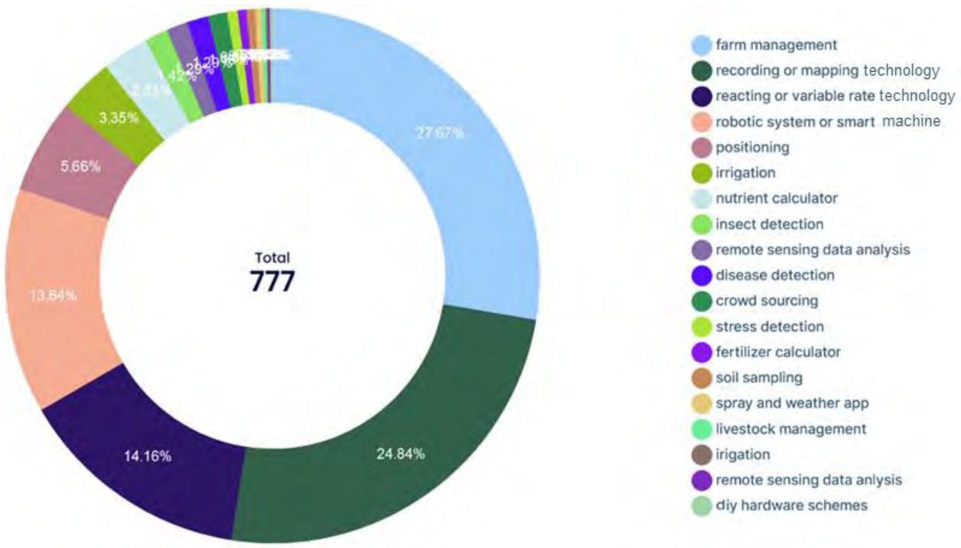

Figure 2 Technology entries provided on the MergData Plattform sorted by 'Category'

In Table 2, an overview of the same technologies is provided summarized for each category in absolute numbers. For some technologies, multiple entries have been used so that the sum of all technology entries in this table does not correspond to the total number of researched technologies.

Technologies were categorized into 17 groups: Insect detection, crowd sourcing, disease detection, DIY hardware schemes, irrigation, farm management, fertilizer calculator, livestock management, nutrient calculator, positioning, reacting or variable rate technology, recording or mapping technology, remote sensing data analysis, robotic system or smart machine, soil sampling, spray and weather app and stress detection. The number of technologies varies between the different categories. For the categories farm management, reacting or variable rate, recording or mapping technology and robotic system or smart machine, the most entries were found because currently there is a strong technological development for improving farm management systems with geographical information

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systems and precision agriculture technologies going on in Europe. In the categories of insect detection, crowd sourcing, disease detection, irrigation, nutrient calculator, positioning and remote sensing data analysis less entries were found but were still quite represented. In contrary, the categories DIY hardware schemes, fertilizer calculator, livestock management, soil sampling, spray and weather app and stress detection were hardly represented with less than or equal to five technologies. They are mostly niche developments but may still be of interest to the specific case of smallholder farmers.

Table 2: Smart Farming technology database results summarized by categories

No	Categories	Technology entries
1	Insect detection	11
2	Crowd sourcing	9
3	Disease detection	10
4	DIY Hardware schemes	1
5	Irrigation	26
6	Farm management	215
7	Fertilizer calculator	4
8	Livestock management	2
9	Nutrient calculator	22
10	Positioning	44
11	Reacting or variable rate technology	110
12	Recording or mapping technology	193
13	Remote sensing data analysis	9
14	Robotic system or smart machine	106
15	Soil sampling	4
16	Spray and weather app	3
17	Stress detection	5

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In the following, the technology categories are discussed individually. In particular, the possibility of the adaptation in the core communities will be considered.

3.2 Proposed technologies for SIA

3.2.1 Insect detection

Several developments are available for insect detection. There are solutions for hive detection in large, precision farms and several solutions for insect traps with species recognition support. The latter can help with farm management and biodiversity assessment. Potential camera-based deep-learning insect traps such as Z-Trap or BEECAM are often equipped with App integration for smartphones and can help to keep track of beneficial or harmful insects. In this way, they could be a step toward improving food security in core communities.

Plant Village Nuru App is an assistant based on artificial intelligence that can identify multiple diseases and insect pests. For example, it is capable of identifying infections by the fall armyworm and combines it with crowd sourcing data integration. With its affordable pricing, its integration of open access platforms and the possibility for language adaptations on a local level, it becomes of high interest for core communities in the SIA project.

3.2.2 Crowd sourcing

Crowd sourcing technologies are certainly the most important category for the SIA project because it was developed specifically for small-scale farming structures in mind. For this category, eight entries were found. The goals of these technologies are often to strengthen the knowledge base of smallholder farmers, build stakeholder networks, and assist in farm management decisions. TSo achieve a high level of dissemination among the target groups, most of these technologies do not require high investment costs.

399# service is an information providing service in Ghana already working. It is specialized for smallholder farmers and works with any kind of mobile phone. The same applies to iCow, a similar information platform via SMS. Here, the farmers register their cows individually via the iCow App and from then on the app supports them with cow husbandry. It is specialized for smallholder farmers. The data collected is shared and everyone is advised on cultivation decisions as needed. So far, the service has been made available in Kenya, Ethiopia and Tanzania.

Another important development is the establishment of farmer-seller networks. In this way, the profit of the harvest and thus food security can be ensured. Examples of such systems are M-Farm or WeFarm, which are offered in Kenya. Slightly different networks are created with the Plantwise app from the Centre for Agricultural Bioscience International (CABI). Here, farmers all over the world, who seek for help, will be connected with local agricultural extension services or trained plant health experts. In this way, diseases can be diagnosed and best practice recommendations can be made directly to the farmer. Another service is Ushahidi's open-source solution, which uses a variety of data inputs (SMS, Twitter, web forms) to collect and analyze simple data. In this way, for example, an overview of the course of a disease spread in the field can be tracked. Furthermore, Plant Village Nuru

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AI, mentioned already in section 3.2.1, shares information via crowd sourcing to other users. One downside is that these technologies need internet access to work properly.

3.2.3 Disease detection

Originally, sensor networks for disease prediction and modeling for species are mainly developed for western farmers. These tools and associated services come with high investment and maintenance costs. Therefore, these sophisticated tools are mainly unattainable for the targeted core communities of the SIA project. However, for regions where smartphones are already widely used with internet access, there are now viable and cost-effective options available. Open source apps can be a good choice for disease detection and prevention. Stress symptoms can also be detected in various field crops. These applications usually store an image and compare it with previously trained artificial neural networks. A representative of this category is, among others, the Plantix app, which globally collects more and more images for training the disease detection algorithms. The App can also analyze cotton, corn, mango, millet, okra, olive and sorghum, among others. Almost all target crops of the SIA project, except for pineapple, can be analyzed. Another option for a broader use is the Xarvio Scouting App, which detects diseases and leaf damages independent from the plant species as well as the Plant Village Nuru AI, mentioned in section 3.2.1, which is capable to detect diseases, for example in cassava crops.

3.2.4 DIY hardware schemes

The DIY Hardware schemes is an example of a niche technology so far. However, 3.2.1 DIY hardware schemes project is a powerful lever to support import-independent, long-lasting agricultural development in the core communities. This unique project offers the possibility to build 50 machines, including tractors, automatic harvesters, or well drilling rigs, making the purchase of these machines much cheaper and at the same time creating the necessary knowledge for repairs and maintenance.

3.2.5 Irrigation

Precision agriculture in the field of irrigation is not a novelty for western farmers. Developments in smart farming include sensor stations for weather recording and hydrological applications (Dacom Online Irrigation Management, Vinduino R3 Sensor Station; John Deere Field Connect), programming or controlling flexible irrigation systems (ART3 Agro; SmartRain App; GROWSMART; Weenat; Agsense app, Irrigamatic, Irrigation Management) or setting up and reading complex sensor networks for the purpose of spatially differentiating soil moisture or plant water content across the site (Digital TDT Soil Moisture Sensor; YARA WATER SENSOR; Soil Moisture Probes; Pro Series Soil Sensor; Sensetion). Also, the adaptive irrigation systems themselves are sold on the western market, e.g. HydroPlus - Smart Remote Management Irrigation System, PESSL INSTRUMENTS PRESSURE SWITCH, Rainbird Products. However, these are often sophisticated systems that are expensive to purchase and operate. Therefore, they are not considered for smallholder farmers.

External consultants are working with farmers in Europe and elsewhere to install precision irrigation on agreed target areas. One agent, for example, is TERRAPRO TECHNOLOGIES or the Dacom Farm

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Intelligence. Such partnerships are also possible on a limited scale for smallholder farmers in Northern and Western Africa.

The partner in the SIA project, BluLeaf, provides the necessary technology for irrigation planning, including a smartphone application for monitoring and displaying the collected data. The Italian company also offers workshops for interested farmers on how to use the new technology. In the further course of the SIA project, BluLeaf will be used in selected core communities and tested for its suitability and adapted if needed.

In addition, technologies such as solar-powered water pumps could be of interest to farmers participating in the SIA project (e.g. Solar Pumping Arateck). They operate independently of the power grid and could lead to savings in labor time where laborious manual irrigation is required.

3.2.6 Farm- or Livestock-management

The category farm management is often mixed with other categories. Since technologies with multiple categories that include farm management are discussed in the respective other sections, only database entries that exclusively carry this feature are discussed in the following.

Often, technologies in this category are used to combine different smart farming technologies (e.g. Nexxtep Technologies; Wi6labs; farm+; Virtual Optimizer Pro; Sensordata applicatie) or to better manage the various tasks of a large farming operation (e.g. CropTrak Solution Platform, INPULSE). Some applications also simplify the optimization of existing vehicle fleets and their interaction (e.g. EASY Farm Telematics, AFS Connect - PLM Connect, SAMSYS-Activity) or create a possibility for remote control of various smart farming devices via the internet (John Deere MyJobConnect package; FarmCommand). In order not to lose track of one's own products from harvest to retail and to be able to display required certificates if necessary, there are also tracking apps such as the Internet-of-Crops™ platform, among others. However, since smallholder farmers in northern and western Africa do not own large fleets of vehicles nor large fields, these technologies are mainly not of interest to the SIA project.

More interesting, however, are technologies that deal with networking farmers with other stakeholders, such as suppliers, consultants, retailers, seed or fertilizer manufacturers. These technologies already exist for the Western market, such as cumalink, and there are some African applications of this type already available (iCow). Farmer-farmer networking, such as *Agrifind: Shared Field Expertise* on the Western market, also provides a helpful source of information, but is closer to the crowd sourcing category. Such networks can also educate on legal issues and answer local inquiries about laws, such as agricultural fertilizer norms. To ensure that the farmers' business model remains more resilient against climate change, external consultants, such as ClimaVista BI from France, provide a cloud-based climate risk management solution could be consulted. Such companies could have a major impact on food security because they can provide projections on the impact of regional climatic changes for farms.

Most livestock technology solutions are designed for large farms with large herds (e.g. FarmRexx) and may be too complicated for smallholder farmers. An interesting service, however, is Cowtribe, which connects local veterinarians with farmers to get them informed about critical conditions or vaccinations. The Cowtribe service is providing contacts, logistics and services for Ghanaian farmers.

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3.2.7 Nutrient calculator

Fertilizer calculation is mostly about how much fertilizer needs to be applied to deliver the right amount of fertilizer based on a soil sample analysis (e.g. Fertilizer Calculator; Organic Calc; Fertilizer removal by crop; Crop nutrient removal calculator; FertiMatch). In some cases, the application rate is also calculated based on sprayer attributes (e.g. Cali Calc). The app Plantix could be of interest for smallholder farmers because it derives fertilizer requirements for plants based on simple smartphone images. Typically, smallholder farmers in Western and Northern Africa cannot afford large amounts of fertilizer. Therefore, there tends to be an undersupply of fertilizers, whereas these calculators aim at optimal fertilization. The CowPoopAnalyzer is another interesting app. The app uses smartphone images to compare cow dung with an online image database to estimate certain nutrient levels. The Yara CheckIT app can also be helpful for smartphone owners, as it detects nutrient deficiencies in plants free of charge. In this way, fertilization can be readjusted at the most critical points.

3.2.8 Positioning

Global Navigation Satellite Systems (GNSS) are widely used in Western agriculture for positioning. They provide, for example, the basis for site-specific applications in precision agriculture. Common and widely used are simple GNSS devices using the bare signals from the different satellite navigation systems (e.g., GPS and GLONASS). They provide low spatial accuracy with a few meters of uncertainty. More advanced systems make use of the correction signals from ground stations with real-time kinematics (RTK), which provide higher spatial accuracy in a range of a few centimeters (e.g., John Deere Radio RTK; The Precision Farming BOX; ISA360). Often, such systems are available as an internal control when selling large agricultural machinery or offered for retrofit (e.g. AutoTrac; Wingssprayer; TRUAS TrueAgriculturalSensing; Farmsat Mapping Application; AutoTrac Vision). Combined with recording and mapping technology some systems can help to keep track of the growth and health status of the crops or other site-specific conditions (e.g. Agriculture Remote Aerial Sensing; Parrot SEQUOIA). In order to keep track of the now numerous systems and their collected georeferenced data, cloud solutions for the storage and clear presentation of the results are already offered on the western market (e.g. Dacom Cloudfarm).

For positioning technologies it can be concluded that this form of support is currently unsuitable for smallholder farmers in West and North Africa. The benefit only arises when the land to be cultivated is very large, which farmers in the core communities do not hold. Such systems are also very expensive to purchase and to operate, as monthly costs are often incurred for services such as subscription offers for e.g. correction signals.

3.2.9 Reacting or variable rate technology

Responding to spatially discrete environmental or plant condition is the key cocept behind precision crop management. In this way, raw materials, such as water or fertilizer, can be saved, while at the same time yields are improved in their quantity and quality, through a more precise demand response. Also spraying agents can be applied precisely, or seedlings planted more accurately. As mentioned in section 3.2.8 Positioning, such on-demand working systems are often directly combined with

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positioning systems. These sophisticated systems are mostly automated and optimized for field crops that are common in the western market. They also develop their strength only with extremely large cultivated areas. Described systems are e.g. CropSpec, DynamicDosePlus, Weenat, ISOBUS PLANTER-Controller or SPREADING LIQUID MANURE. These kind of systems are also available as add on technology for outdated hardware (Smart Ball Valve; ISOBUS DISTANCE-Control I und II; TARGIS-VRA; Delvano Nozzle Control) but have high investment costs. Also, there are online in cloud calculation tools such as Agriculture Remote Aerial Sensing, which can help optimizing, e.g. sprayer agents or fertilizer inputs, using remote data. Those technologies rely on monthly payments, which are hard to earn or justify for African smallholder farmers. However, there are some pricy alternatives such as the Spray Calc system. But even these systems require mechanized, GNSS-located spreaders. However, because such systems are not usually found in the core communities, these cost-free solutions are not applicable either.

3.2.10 Recording or mapping technology

Recording or mapping technologies have a high overlap with sections 3.2.9 reacting or variable rate technology and 3.2.6 farm management, as these systems are often combined. This results in decision-support applications that can also provide an overview of past developments of an individual farmers agricultural land, and thus present trends in a clearer way.

Classic applications in the western agricultural market are the recording and mapping of small-scale climatological differences using mobile climate stations (e.g. Rainwise, CimAGRO; TWRS Wireless RainSensor), the sub-area-specific storage of yields (e.g. HarvestDoc) or the usually legally required documentation of crop protection spraying (e.g. RRXtend Spray app). Furthermore, various devices are offered for the determination of sub-area-specific plant health. For such monitoring, there are adapted hyperspectral cameras (e.g. Hyperspectral camera for plant health monitoring), sophisticated drone solutions (e.g. AIRPHEN, AgroDrone) or ground-based autonomous robots (e.g. PHENOMOBILE).

Another application is soil nutrient calculators (e.g. Solum; SoilCares Scanner). They estimate the current soil nutrient content based on the management decisions made and the yields achieved. The following management decisions can then also be derived from this.

A similar tool of interest to the SIA project would have been the compostmeter, for determining the organic carbon content of composted household residues. Unfortunately, the associated project has been stopped, making it currently difficult to obtain the necessary measuring probes. Combined systems for recording soil temperature, soil moisture and soil salinity (e.g. SOIL MOISTURE SENSOR; Sentek Soil Moisture Monitoring) could also be of interest to smallholder farmers in West and North Africa. By analyzing soil parameters over a long period of time, processes that are difficult to reverse, such as the salinization of fertile soil, can be detected in advance and prevented through appropriate management.

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3.2.11 Remote sensing data analysis

Remote sensing data from various satellite systems, some of which are freely available, offers the possibility of providing farmers with evaluation algorithms for these data. Specializing in agricultural applications, according to the companies, plant health, stress influences or plant diseases can be detected and thus management decisions can be derived at an early stage. The underlying satellite data is sometimes even collected on a daily basis (e.g. Agriquest Global Monitoring; Cropwise Imagery, ANA - Agricultural Nutrient Assistant). The Space4good system is another such development. In addition to applications for precise agriculture, it also offers trained systems for the assessment of ecosystem services, which is why it is particularly suitable for use in the SIA project.

Another application is the creation of topographic maps (e.g. land leveling) which can also be combined with spatially resolved soil mapping (e.g. TrimbleSoil Information System). Furthermore, there are applications that facilitate the acquisition of remotely sensed data. Flight planning of a drone can be automated (e.g. FieldAgent app; Atlas Flight) or satellite data can be automatically cropped and stored based on entered field boundaries (e.g. SatHarvest API).

Autonomous satellite terminals can help connecting remote areas to the internet (e.g. MF 400 IoT Satellite bridge). In this way smart farming devices, which often rely on internet connections, can be made accessible for icloud analyzing or storing. This can also be a solution for remote communities without internet access to enable the use of open-source app technology.

3.2.12 Robotic system or smart machine

One of the biggest recent developments occurred in the robotic system, or smart machine category. With ever increasing computing power, even of mobile systems, and the development of trained artificial intelligences for agricultural applications, numerous technical solutions have become possible. Agricultural machines were redesigned or upgraded to be controlled remotely (e.g. icut vision), or to set driving parameters themselves (e.g. iTEC Pro; Tractor Implement Automation). Sensor inputs for precision farming approaches can now be evaluated directly while driving and the smart machine reacts without further intervention by the farmer (e.g. Rometron WEEDit; FertiSystem; See & Spray; Autonomous robot weeder). Land grading (e.g. iGrade) or adaptations of agricultural spraying systems (e.g. Shielded sprayers, Delvano Dual Fluid Control; PiiX - Direct injection Unit for sprayers) as well as planting robots (e.g. Contour Farming), have also been developed. Another application is smart weather analysis stations (e.g. Smart Connect Wireless Weather Sensor; TRS Wired RainSensor). To keep track of the collected information and to pool the resulting knowledge, some systems deal with the display and combination of data from multiple sources (e.g. HummBox, SMART430®; My.Luda.Farm; FLIPAGRI; IsoMatch Tellus). In general, the developers of these technologies assume that agricultural machinery, sensors, or at least sufficient computing power and a good infrastructure for power and internet connection already exists in the farm. Thus, the technologies in this category are predominantly not well suited for farmers in the targeted core communities.

An exception to this could be drone applications (UAV), as here a large number of farmers could benefit from the collected data at a relatively low cost. The development of smart UAV and associated software (e.g. eBee SQ; Stratus, Sprinkler drone) could benefit farmers in West and North Africa as well as the development of service providers that offer UAV applications to the farmers.

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To reduce the downtime and to improve the distribution of tractors, a start-up in Nigeria offers the Hello Tractor app. Farmers can book tractor times, tractor owners receive orders and there are options for fleet maintenance. The IoT concept therefore connects small farmers with the necessary service providers and makes effective use of existing local hardware.

3.2.13 Soil sampling

Automated soil sampling systems make it easier for Western farmers to distribute samples to ensure sufficient coverage and uniform distribution of measurement points. Automated systems are available that reduce the labor input needed for manual sampling (e.g. AutoProbe Automated Soil Sampling Technology; falcon automated soil sampling). So far, these systems have not addressed farmers in western and northern Africa. Soil sampling apps (e.g. Sirrus; Soil Test Pro) are better suited for improving soil sampling. However, they require smartphone or tablet technology and a sufficient connection to the internet. These software solutions help with equipment procurement, sampling and finding a suitable laboratory for soil analysis.

3.2.14 Spray and weather app

Since many agricultural management decisions depend on climate data, in western agriculture the prevailing microclimate is measured mainly by means of climate stations installed in the field. These stations can also be used to improve the general weather forecast (e.g. climate monitoring tools). However, the quality of such a forecast depends on the density of measuring stations. Therefore, app technology for forecasting weather in Africa can probably only work with a reduced accuracy. Nevertheless, in regions with the required technology and infrastructure, important events may be estimated. When developed for agricultural purposes, weather apps often provide recommendations for pesticide spraying or other decisions (e.g. RRXtend Spray app).

3.2.15 Stress detection

One smart technology being developed to detect early stress indicators in western agriculture is the use of high-resolution UAV imagery in addition to climate stations (e.g., Climate Monitoring tools) or dendrometers (e.g., PESSL INSTRUMENTS DENDROMETER). The high sensor flexibility plays a major role, as does the advantageous ratio between spatial resolution and area coverage per flight. Many service providers develop on the UAV use in agriculture now, like e.g. crop stress mapping or yield estimation (e.g. AgroDrone, AgriSens; TRUAS TrueAgriculturalSensing). Communities in western and northern Africa, such as those involved in the SIA project, could contract third-party providers to fly the areas of several smallholders to make this technology available.

For extended analyses of the recorded data, aggregating and analyzing systems are used (e.g. Sigfox; Integrated Analytics Platform; cropwin). However, these are likely to be too expensive for the operation by smallholder farmers. There are, however, smart phone app based alternatives for these servoces, which are affective and free of charge. They use the smartphone as sensor, for example, by detecting plant stresses on the basis of RGB imagery (e.g. Android-based rice leaf color analyzer). The Xarvio Scouting app is claimed to be able to determine the nitrogen content of a leaf using smartphone

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imagery. Of course, this requires smartphone technology as well as a stable internet connection, as these programs compare the images taken with an online database.

3.2.16 Conclusion

Technologies suitable for smallholder farmers in North- and West Africa can be either: relatively simply to implement, granting access to fast benefits; can be more extensive, such as for determining resilient food security under climatic change; or can increase yields and profits in general. Simple technologies to be introduced in the agricultural management of the targeted core communities should certainly not have high demands on the computing power. For remote regions, it would be optimal to be independent of a continuous power supply and internet connection. Furthermore, proposed technologies must not lead to high investment or operating costs. However, even free apps could lead to inappropriately high investment costs because it cannot always be assumed that modern smartphones will be available. Here, initiatives can help with the investments for some of the farmers.

Simple technologies have been partially already implemented, e.g. for crowd sourcing tools using mobile phones to support smallholder farmers, for better farm management or networking. Free app technology and remote sensing from UAV and satellites deliver a timely assessment of plant health and nutrition status. Smallholder field structures are very heterogeneous and field sizes are relatively small so that remote sensing approaches must provide a high-spatial resolution, in order to deliver data that can be evaluated profitably. As shown in chapter 2.3 this approach can be suitable.

More problematic are technologies for variable rate technologies or robotic systems, which are highly developed systems that could increase yields while reducing inputs. However, this would include high investment cost for implementation. For smallholder farmers, more interesting technologies would include apps that help to determine stress symptoms, low budget fertilizer maps generated by remote sensing data, or low-cost irrigation information systems. Machine sharing or provision of agricultural services would also be a viable option to reduce investment costs and facilitate access to more sophisticated technology at the same time. For example, the use of drones could be disseminated by a network of agricultural service providers.

However, whether a technology can be implemented does not ultimately determine the success of the adoption by the smallholder farmers. To be able to offer useful targeted technologies, it is necessary to understand the needs and concerns of local smallholders. Therefore, technological implementation must be aware of local requirements, and introduced with professional support and training. Otherwise, there is a risk of a low adoption rate and a lack of success of a program. Moreover, there is a need to understand cultural appreciation and conditions to introduce and adapt technologies.

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4. Companies, Initiatives and Projects

4.1 General database summary (Companies, Initiatives, Projects)

The published database contains 289 companies that produce and develop technology or software in the field of smart farming. All contact details of the listed companies were collected and published on the MergData platform.

In addition, 30 initiatives and projects were included in the database with information on the name, the organizing institute and its headquarters, the focus of the project as well as a brief description of the project and a weblink to the project's respective online presence.

Interesting projects within the framework of the SustInAfrica project deal, for example, with long-term and cost-effective soil improvement through legume-based nitrogen enrichment for smallholder farmers (*N2Africa*) or with scaling up successfully adopted technologies leading to large-scale production increases in Liberia and the Congo (*Africa Feeding Africa/ Technologies for Africa's Agricultural Transformation*). The Smallholder Agriculture Development Project promotes information transfer to smallholder farmers for the purpose of increasing the market value of crops. UAV service providers (*Transforming Africa's agriculture: Eyes in the sky, smart techs on the ground*) also serve to provide farmers with training and information on drone use. Another project focused on operating their own low-cost developments (*Beyond flying UAVs in smallholder farms*). In the *PlantVillage Nuru* project, an AI-based smallholder APP was developed against pest and diseases.

Many projects deal with networking between farmers and stakeholders and with information dissemination to farmers for the purpose of improved profitability of products or for possible credit loans (*Agricultural Research and Training Project; Financial Inclusion for Smallholder Farmers in Africa Project*). Networks among farmers are also being strengthened and crowd sourcing approaches can even be used to specify weather forecasts at low cost (*Ranet*). Another area of work for projects and initiatives is increasing the resilience of smallholder farming to climate change. The *West African Initiative for Climate-Smart Agriculture* is improving information sharing to help transform agricultural production towards a climate smart agriculture approach. A similar approach is followed by the *Program for Climate-Smart Livestock Systems* in the livestock sector. Projects such as *INSARD* and the *Competitive African Cotton Initiative* are working to adapt future technologies and policy reforms to the needs of smallholder farmers.

4.1 Collaboration to Smart4All Project

In addition to the aggregated projects in the database, a collaboration with the EU-funded SMART4ALL project (Project Number: 872614) has been established. SMART4ALL builds capacity amongst European stakeholders via the development of self sustained, cross-border experiments that transfer knowledge and technology between academia and industry. It targets customized low energy computing (CLEC) cyber-physical systems (CPS) and the IoT and combines a set of unique characteristics that join together under a common vision different cultures, different policies, different geographical areas and different application domains. SMART4ALL brings a new paradigm for revealing “hidden innovation treasures” from south east Europe (SEE) and helping them to find the path to market via new, innovative commercial products. As part of its strategy, the project will develop and maintain an active network of digital innovation hubs (DIHs) across SEE for supporting academics, startups, small and medium scale enterprises (SMEs), and mid-caps entering the digitization era. The

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mechanisms for achieving this are the design and implementation of 88 cross-border pathfinder application experiments (PAEs) that will be executed by the consortium members and by 3rd party consortia (academics, companies and mid-caps). The latter will be supported via well-defined regular open calls and will have a day by day coaching by SMART4ALL consortium for boosting the research ideas to successful products. PAEs will be actively supported by SMART4ALL DIH cluster throughout and after their execution. The targeted application areas are domains that are not adequately represented in current smart anything everywhere initiative (SAE) projects and include digitized environment, digitized agriculture, digitized anything and digitized transport. SMART4ALL introduces also the concept of marketplace-as-a-service (MaaS) that acts as one-stop-smart-stop of SMART4ALL DIH cluster for offering tools, services, platforms based mainly on open sources technologies as well as technology suppliers-adopter matchmaking capabilities customized to the four thematic pillars of the project. Finally, SMART4ALL plans horizontal activities that will support the Digital Skills Agenda of European Commission (EC) and the support of sensitive social groups via ideas and products that have significant impact on their lives. In collaboration with SustInAfrica, the collected databases from both projects are linked to each other. In that way, combined findings are accessible for interested stakeholders browsing one of the databases. In SMART4ALL a database entry for the SustInAfrica database is created and in SustInAfrica a web URL to the SMART4ALL database is given.

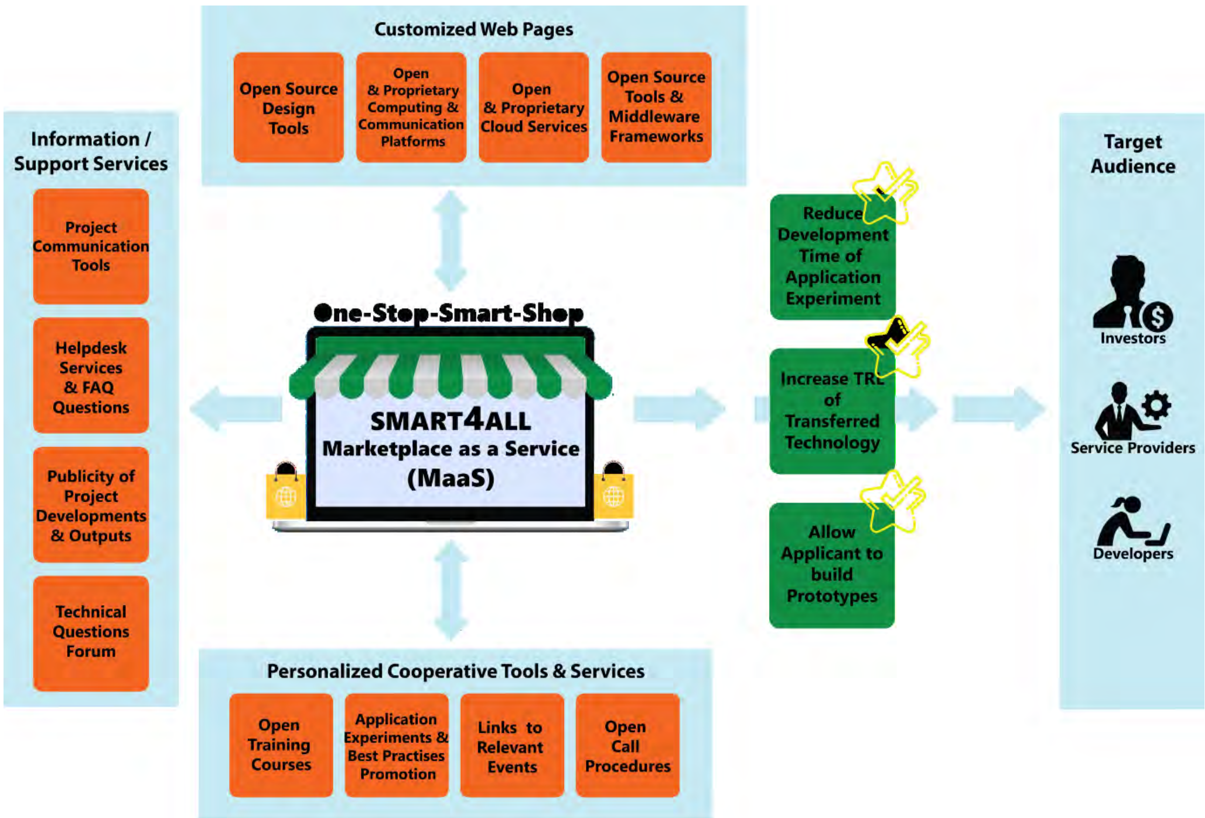

Figure 3: SMART4ALL Marketplace as a Service Conceptual Architecture

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5. Database

5.1 Objective of the database

The database aims to provide an overview of the latest developments in agricultural processes and applications in the field of smart farming and monitoring technologies. The database was designed and organized by Farmerline and integrated in their Mergdata Platform. The database will be linked to information managed within Farmerline`s Mergdata platform on farming systems. The Mergdata platform provides a farm data management tool for gathering and analyzing information on farmers, farms and treatment at every stage of the supply chain. The integrated smart farming and monitoring database is openly available and can be easily browsed to extract relevant information for the stakeholders. Furthermore, stakeholders can add entries regarding smart farming technologies interesting for smallholder farmers of the core communities. Researcher partners in the SustInAfrica project are in addition able to add entries of related scientific publications in the database.

5.2 Setup process of the database

Mergdata is a data collection, dissemination, and analytics platform built by Farmerline that will support the SustInAfrica project. Mergdata is built upon a reliable and centralized database system; to facilitate the electronic capture, storage (i.e. data secure system) and utilization of stakeholder data and conduct surveys as well as join and visualise spatial and non-spatial information. Mergdata has the capability to aggregate data related to customer profiles, surveys, maps, traceability, and other vital metrics. The application is web-based and is accompanied by an Android application to be used by field agents and enumerators. The web platform provides users with the tools to create and analyse data collected with the Android app. Data entry while considering protection of personal data can be done in three ways, either: I) using the Mergdata web form of Farmerline (Annex 1), or II) using the Android app or III) using the Excel import (Annex 2) and upload the information directly to Mergdata. The Mergdata Web Platform runs in a web browser. It is compatible with browsers like Google Chrome, Mozilla Firefox, Safari, Opera, and Microsoft Edge etc. It is a web-based application, so it can run on any device with browser capability e.g., desktop computers and laptops. Mergdata Android app runs on all Android devices (mobile and tablet) with the minimum software version of Android 5 (Lollipop).

5.2 Access to database

In the SustInAfrica project, the information among consortium participants or other stakeholders will be accessed through a web portal and/or application programming interface (API) integration for applications to exchange data and information automatically. Users require a username and password to access the platform. Each partner will have access to add and consult data. Data introduction will be done through a set of sequential webforms that present the fields necessary for data entry (See Annex 3). The following link to the webform can be circulated for stakeholders to voluntarily provide their details; Stakeholders Database

Partners can also download the Android app from the Google Play store (see link below) and login with the access details provided to be able to fill in the form. Below is the link to the Mergdata android app on Google Play Store (https://play.google.com/store/apps/details?id=com.mergdata).

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7. Appendix

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Annex 1 Sub categories chosen for recent research activities

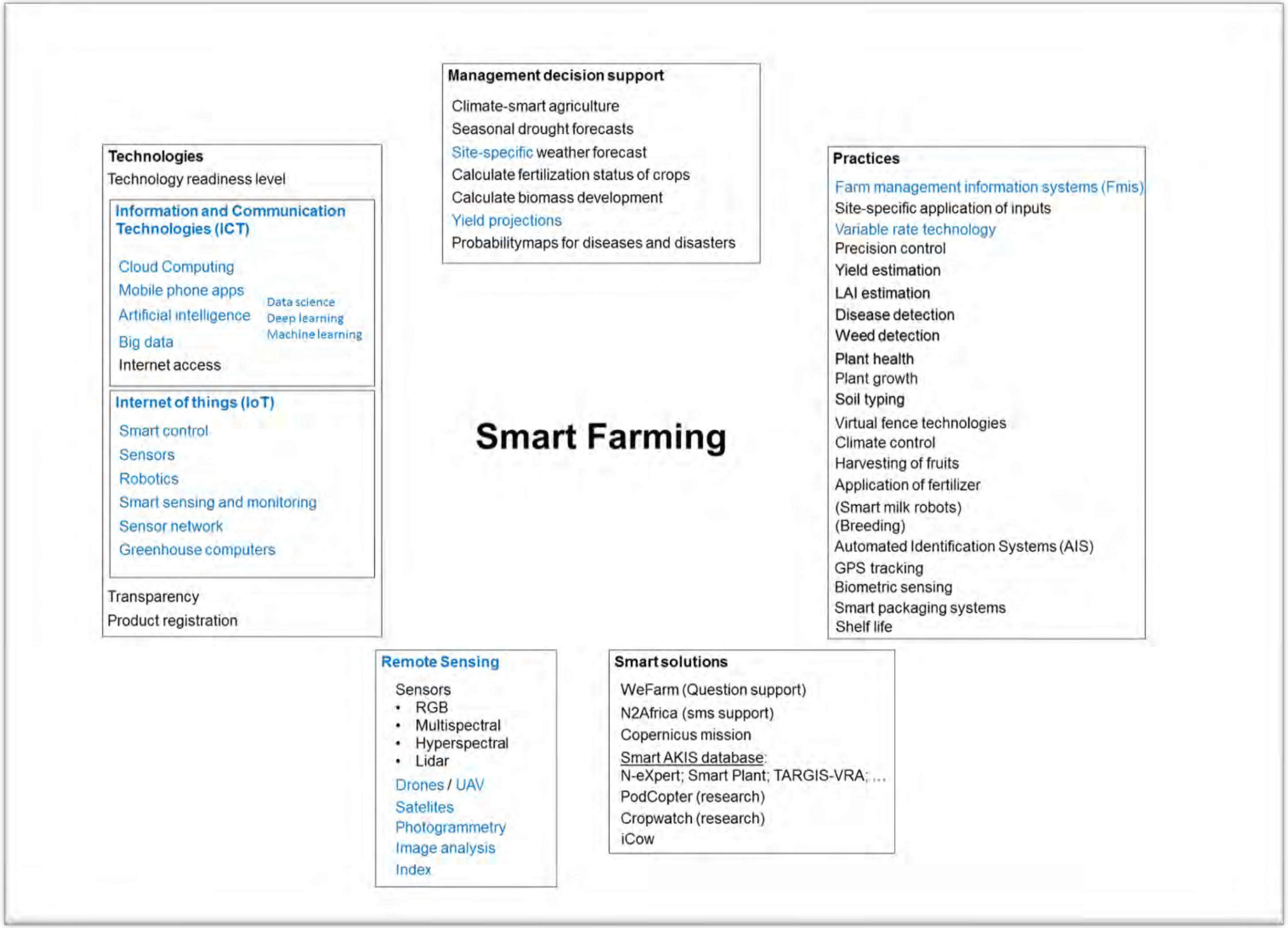

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Figure 4. Keyword-Mindmap for recent research investigation of smart farming. (Blue color indicates chosen keywords after discussion with several partners (ATB, BOKU))

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Annex 2 Findings for recent research activities in ISI Web of Knowledge all collections

Table 3. Sub keywords, filters, search strings and findings for ecosystem services in the Web of Knowledge Core collection.

Smart Farming - Subkeyword	Main Keyword (Targeted variable)	Filter	Sub-search strings	with Filter (16.02.2021)	with filter + small holder (16.02.2021)	Searchstring with small holder (23.03.2021)
- None -	"ecosystem service"	Agri*; Farm*; Horti*; livestock; crop; field; orchard; (small holder)		23465	513	TS= ("ecosystem service" OR "ecosystem services") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Information and Communication Technology / ICT				9	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=(ICT OR "Information and communication technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Smart farming				4	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("Smart farming") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
4.0 technology				0	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("4.0 technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Precision agriculture / Precision farming				61	2	TS= ("ecosystem service" OR "ecosystem services") AND TS=("precision agriculture" OR "precision farming") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Cloud Computing				13	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("cloud computing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Mobile phone / App				19	1	TS= ("ecosystem service" OR "ecosystem services") AND TS=("mobile phone" OR App) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Artificial Intelligence (AI)				60	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("artificial intelligence" OR AI) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Big Data				43	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("big data") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Data Science				2	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("data science") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Deep learning				14	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("deep learning") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Machine learning				80	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("machine learning") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

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Internet of things / IOT				2	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("internet of things" OR IOT) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Smart control / smart technology				0	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("smart control" OR "smart technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Sensor				87	1	TS= ("ecosystem service" OR "ecosystem services") AND TS=("sensor") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Robotics				3	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("robotics") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
smart sensing / smart monitoring			disease detection, weed detection, plant health	40	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("smart sensing" OR "smart monitoring" OR "disease detection" OR "weed detection" OR "plant health") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Sensor network				2	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("sensor network") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Crowd sourcing				2	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("crowd sourcing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Greenhouse computer				0	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("greenhouse computer") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Site specific				247	3	TS= ("ecosystem service" OR "ecosystem services") AND TS=("site specific") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Variable rate				2	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("variable rate") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Projection / Prediction				783	7	TS= ("ecosystem service" OR "ecosystem services") AND TS=(projection OR prediction) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Farm management information system / FMIS			Yield estimation, LAI estimation,	10	2	TS= ("ecosystem service" OR "ecosystem services") AND TS=("farm management information system" OR "FMIS" OR "yield estimation" OR "LAI estimation") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Remote Sensing				1463	22	TS= ("ecosystem service" OR "ecosystem services") AND TS=("remote sensing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

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Drone / UAV				48	1	TS= ("ecosystem service" OR "ecosystem services") AND TS=("drone" OR "UAV") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Satellite				862	10	TS= ("ecosystem service" OR "ecosystem services") AND TS=("satellite") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Photogrammetry				27	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("photogrammetry") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Image Analysis				88	2	TS= ("ecosystem service" OR "ecosystem services") AND TS=("image analysis") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Image recognition				14	1	TS= ("ecosystem service" OR "ecosystem services") AND TS=("image recognition") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Spectral index				2	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("spectral index") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Vegetation index				243	3	TS= ("ecosystem service" OR "ecosystem services") AND TS=("vegetation index") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
LiDAR				179	2	TS= ("ecosystem service" OR "ecosystem services") AND TS=("LiDAR" OR "lidar" OR "LIDAR") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Ultrasonic				6	0	TS= ("ecosystem service" OR "ecosystem services") AND TS=("ultrasonic") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

Table 4 Sub keywords, filters, search strings and findings for productivity in the Web of Knowledge Core collection.

Smart Farming - Subkeyword	Main Keyword (Targeted variable)	Filter	Sub-search strings	with Filter (16.02.2021)	with filter + small holder (16.02.2021)	Searchstring with small holder (23.03.2021)
- None -	productivity	Agri*; Farm*; Horti*; livestock; crop; field; orchard; (small holder)		261396	4338	TS= (productivity) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Information and Communication Technology / ICT				316	28	TS= ("productivity") AND TS=(ICT OR "Information and communication technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Smart farming				61	2	TS= ("productivity") AND TS=("Smart farming") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
4.0 technology				0	0	TS= ("productivity") AND TS=("4.0 technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

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Precision agriculture / Precision farming				1144	13	TS= ("productivity") AND TS=("precision agriculture" OR "precision farming") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Cloud Computing				83	0	TS= ("productivity") AND TS=("cloud computing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Mobile phone / App				254	17	TS= ("productivity") AND TS=("mobile phone" OR App) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Artificial Intelligence (AI)				1021	32	TS= ("productivity") AND TS=("artificial intelligence" OR AI) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Big Data				193	5	TS= ("productivity") AND TS=("big data") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Data Science				19	0	TS= ("productivity") AND TS=("data science") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Deep learning				117	2	TS= ("productivity") AND TS=("deep learning") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Machine learning				386	4	TS= ("productivity") AND TS=("machine learning") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Internet of things / IOT				234	1	TS= ("productivity") AND TS=("internet of things" OR IOT) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Smart control / smart technology				25	2	TS= ("productivity") AND TS=("smart control" OR "smart technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Sensor				1829	4	TS= ("productivity") AND TS=("sensor") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Robotics				195	1	TS= ("productivity") AND TS=("robotics") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
smart sensing / smart monitoring			disease detection, weed detection, plant health	451	4	TS= ("productivity") AND TS=("smart sensing" OR "smart monitoring" OR "disease detection" OR "weed detection" OR "plant health") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Sensor network				99	1	TS= ("productivity") AND TS=("sensor network") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Crowd sourcing				6	0	TS= ("productivity") AND TS=("crowd sourcing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

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Greenhouse computer				0	0	TS= ("productivity") AND TS=("greenhouse computer") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Site specific				1796	55	TS= ("productivity") AND TS=("site specific") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Variable rate				200	0	TS= ("productivity") AND TS=("variable rate") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Projection / Prediction				7452	77	TS= ("productivity") AND TS=(projection OR prediction) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Farm management information system / FMIS			Yield estimation, LAI estimation,	175	7	TS= ("productivity") AND TS=("farm management information system" OR "FMIS" OR "yield estimation" OR "LAI estimation") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Remote Sensing				4191	50	TS= ("productivity") AND TS=("remote sensing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Drone / UAV				210	3	TS= ("productivity") AND TS=("drone" OR "UAV") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Satellite				3367	36	TS= ("productivity") AND TS=("satellite") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Photogrammetry				64	0	TS= ("productivity") AND TS=("photogrammetry") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Image Analysis				407	1	TS= ("productivity") AND TS=("image analysis") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Image recognition				64	1	TS= ("productivity") AND TS=("image recognition") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Spectral index				48	0	TS= ("productivity") AND TS=("spectral index") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Vegetation index				1732	15	TS= ("productivity") AND TS=("vegetation index") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
LiDAR				239	0	TS= ("productivity") AND TS=("LiDAR" OR "lidar" OR "LIDAR") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Ultrasonic				187	0	TS= ("productivity") AND TS=("ultrasonic") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

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Table 5 Sub keywords, filters, search strings and findings for profitability in the Web of Knowledge Core collection.

Smart Farming - Subkeyword	Main Keyword (Targeted variable)	Filter	Sub-search strings	with Filter (16.02.2021)	with filter + small holder (16.02.2021)	Searchstring with small holder (23.03.2021)
- None -	Profitability	Agri*; Farm*; Horti*; livestock; crop; field; orchard; (small holder)		44089	1077	TS= (profitability) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Information and Communication Technology / ICT				45	0	TS= ("profitability") AND TS=(ICT OR "Information and communication technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Smart farming				11	0	TS= ("profitability") AND TS=("Smart farming") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
4.0 technology				0	0	TS= ("profitability") AND TS=("4.0 technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Precision agriculture / Precision farming				478	4	TS= ("profitability") AND TS=("precision agriculture" OR "precision farming") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Cloud Computing				27	10	TS= ("profitability") AND TS=("cloud computing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Mobile phone / App				30	1	TS= ("profitability") AND TS=("mobile phone" OR App) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Artificial Intelligence (AI)				394	11	TS= ("profitability") AND TS=("artificial intelligence" OR AI) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Big Data				42	1	TS= ("profitability") AND TS=("big data") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Data Science				0	0	TS= ("profitability") AND TS=("data science") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Deep learning				10	0	TS= ("profitability") AND TS=("deep learning") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Machine learning				92	37	TS= ("profitability") AND TS=("machine learning") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Internet of things / IOT				36	0	TS= ("profitability") AND TS=("internet of things" OR IOT) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

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Smart control / smart technology				1	0	TS= ("profitability") AND TS=("smart control" OR "smart technology") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Sensor				215	0	TS= ("profitability") AND TS=("sensor") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Robotics				23	0	TS= ("profitability") AND TS=("robotics") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
smart sensing / smart monitoring			disease detection, weed detection, plant health	38	1	TS= ("profitability") AND TS=("smart sensing" OR "smart monitoring" OR "disease detection" OR "weed detection" OR "plant health") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Sensor network				16	0	TS= ("profitability") AND TS=("sensor network") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Crowd sourcing				0	0	TS= ("profitability") AND TS=("crowd sourcing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Greenhouse computer				0	0	TS= ("profitability") AND TS=("greenhouse computer") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Site specific				606	21	TS= ("profitability") AND TS=("site specific") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Variable rate				185	0	TS= ("profitability") AND TS=("variable rate") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Projection / Prediction				999	50	TS= ("profitability") AND TS=(projection OR prediction) AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Farm management information system / FMIS			Yield estimation, LAI estimation,	11	1	TS= ("profitability") AND TS=("farm management information system" OR "FMIS" OR "yield estimation" OR "LAI estimation") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Remote Sensing				147	1	TS= ("profitability") AND TS=("remote sensing") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Drone / UAV				19	0	TS= ("profitability") AND TS=("drone" OR "UAV") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Satellite				99	0	TS= ("profitability") AND TS=("satellite") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Photogrammetry				2	0	TS= ("profitability") AND TS=("photogrammetry") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

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Image Analysis				29	0	TS= ("profitability") AND TS=("image analysis") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Image recognition				3	0	TS= ("profitability") AND TS=("image recognition") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Spectral index				1	0	TS= ("profitability") AND TS=("spectral index") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Vegetation index				39	0	TS= ("profitability") AND TS=("vegetation index") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
LiDAR				7	0	TS= ("profitability") AND TS=("LiDAR" OR "lidar" OR "LIDAR") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")
Ultrasonic				22	0	TS= ("profitability") AND TS=("ultrasonic") AND TS=(Agri* OR Farm* OR Horti* OR "livestock" OR crop OR field OR orchard) AND TS=(smallholder OR "small holder")

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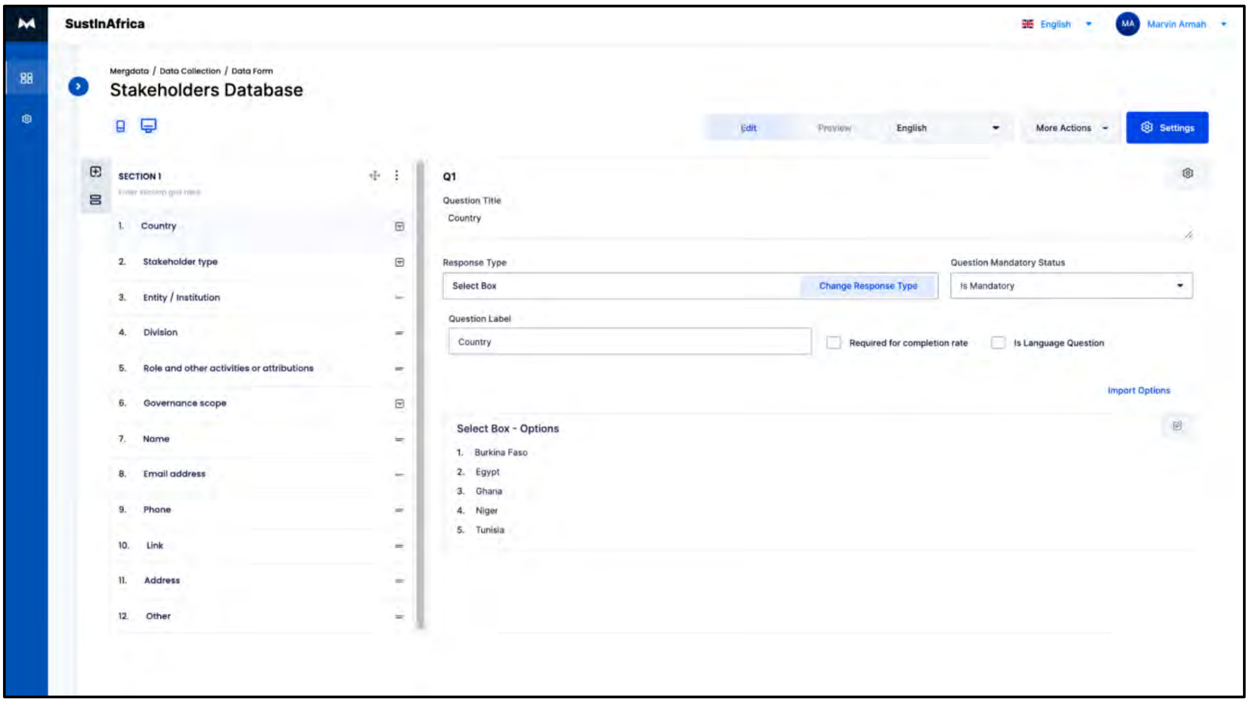
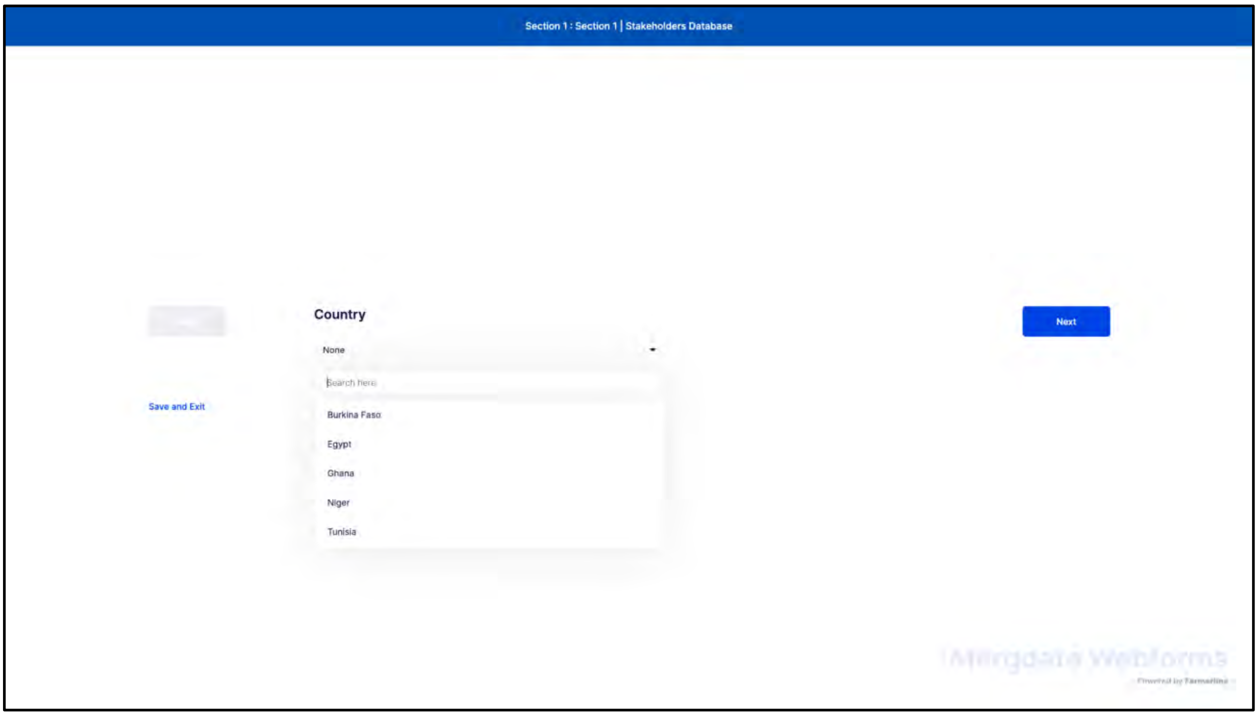
Annex 3: Mergdata database (webforms)

Stakeholders Database:





Link to Stakeholders Database: [Stakeholders Database]

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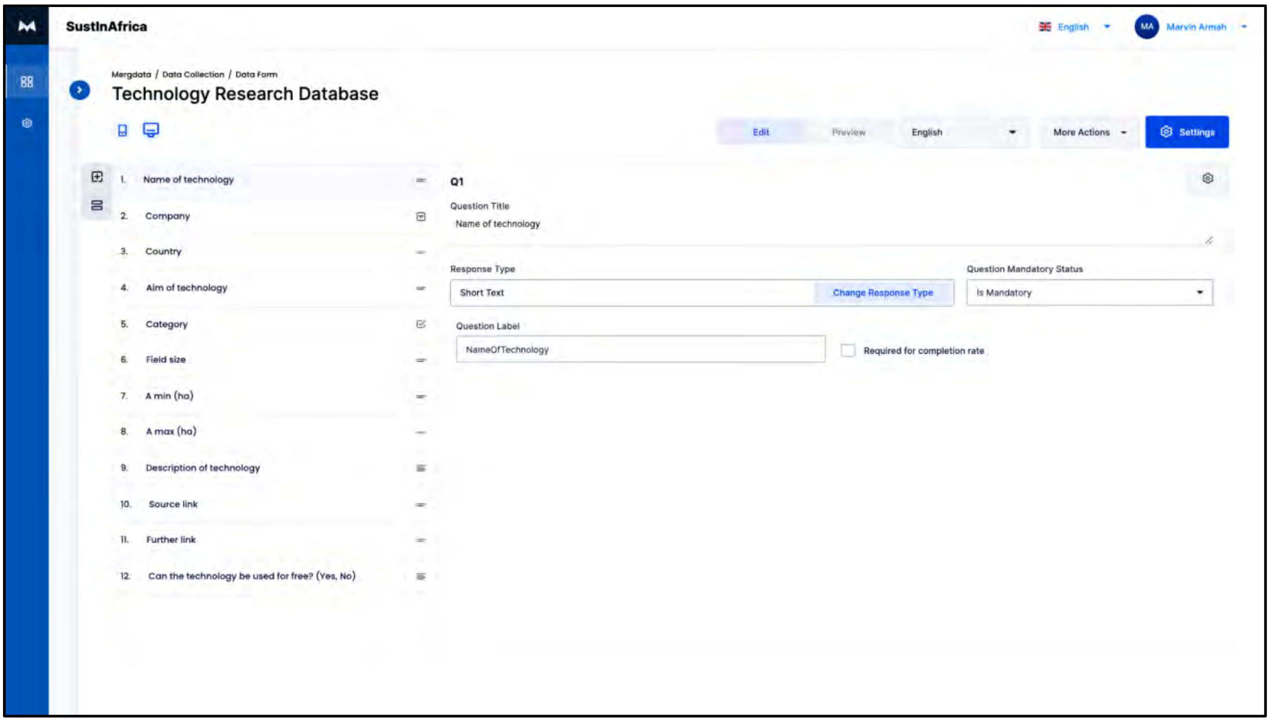
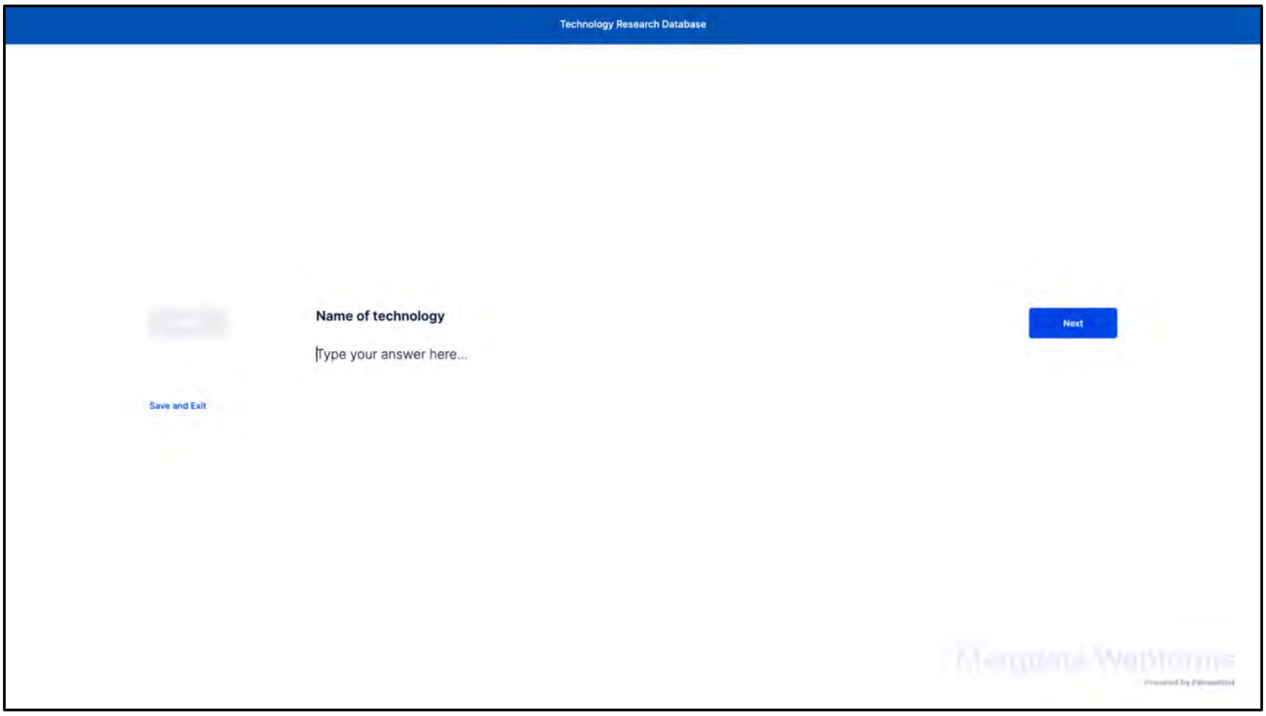
Technology Research Database





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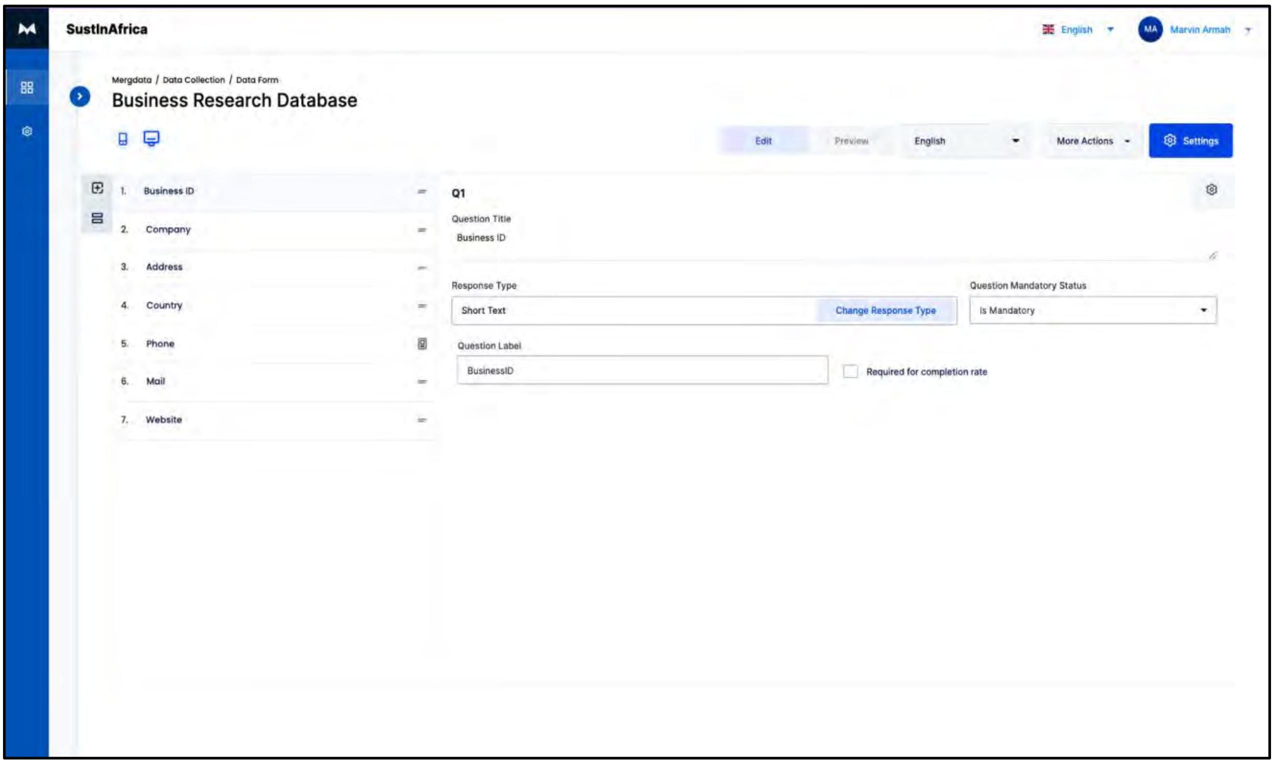
Link to Technology Research Database: Technology Research Database

Business Research Database



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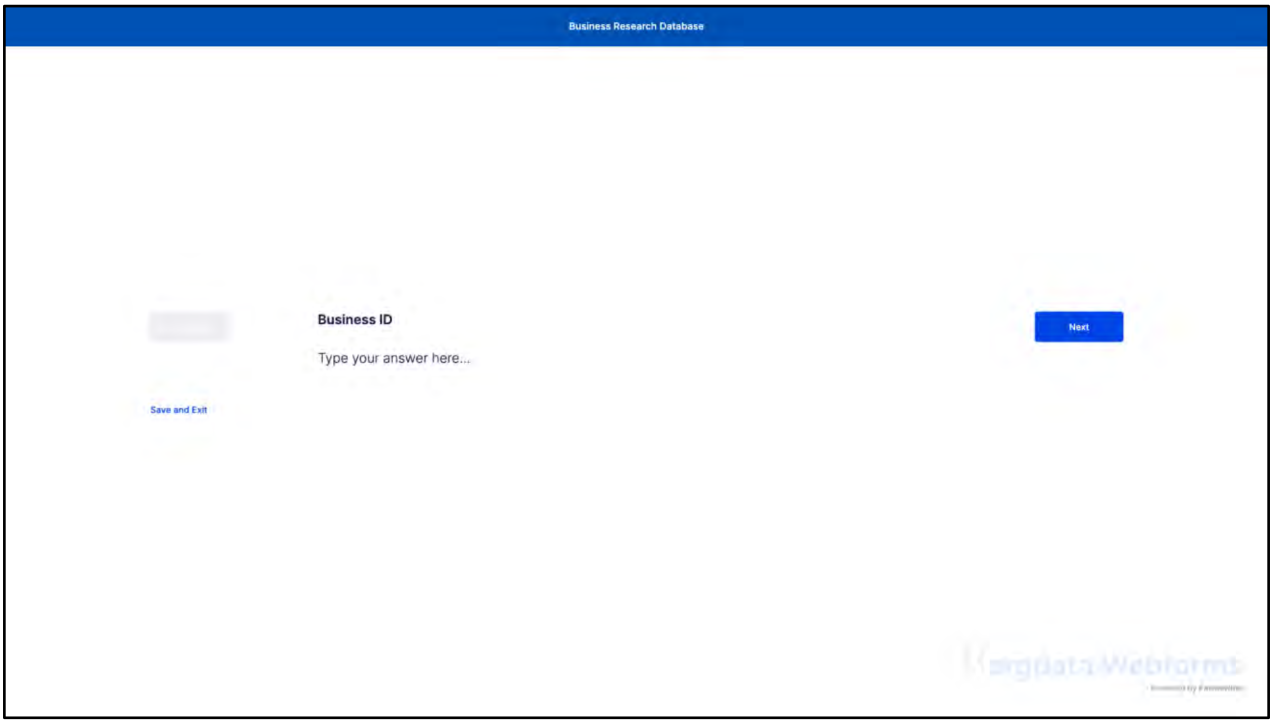
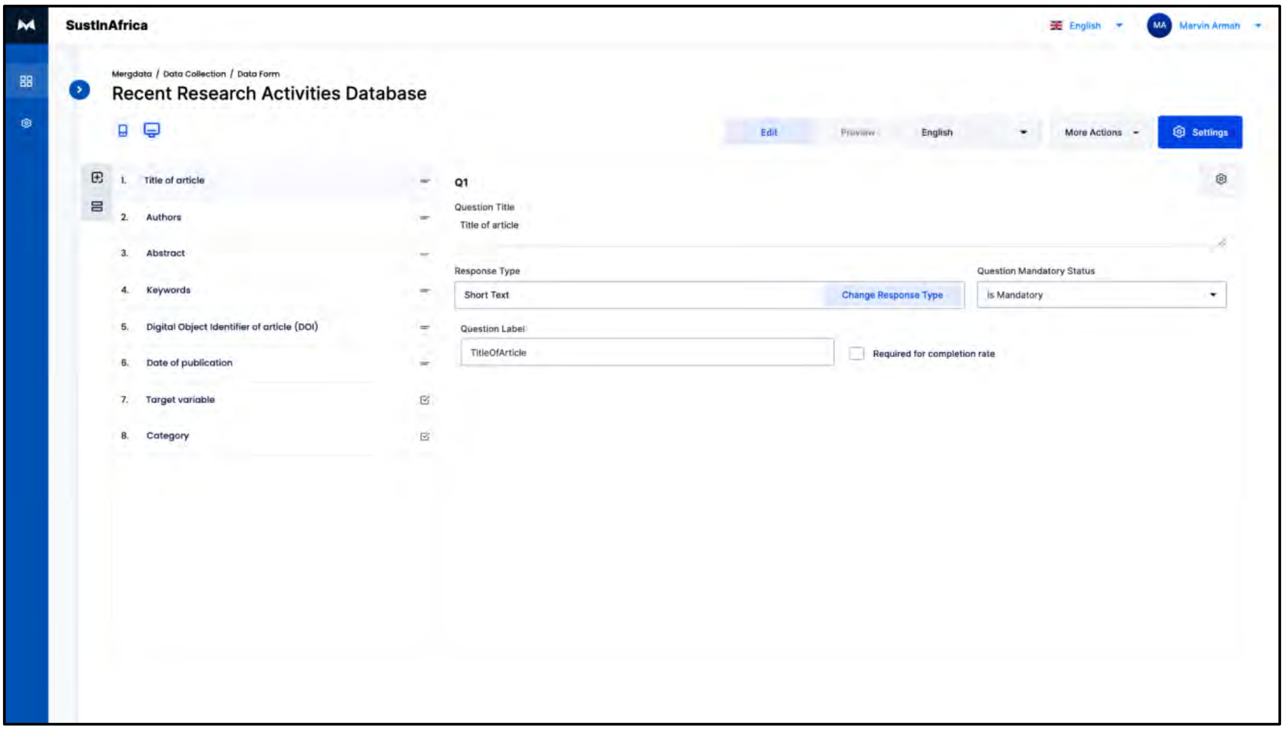
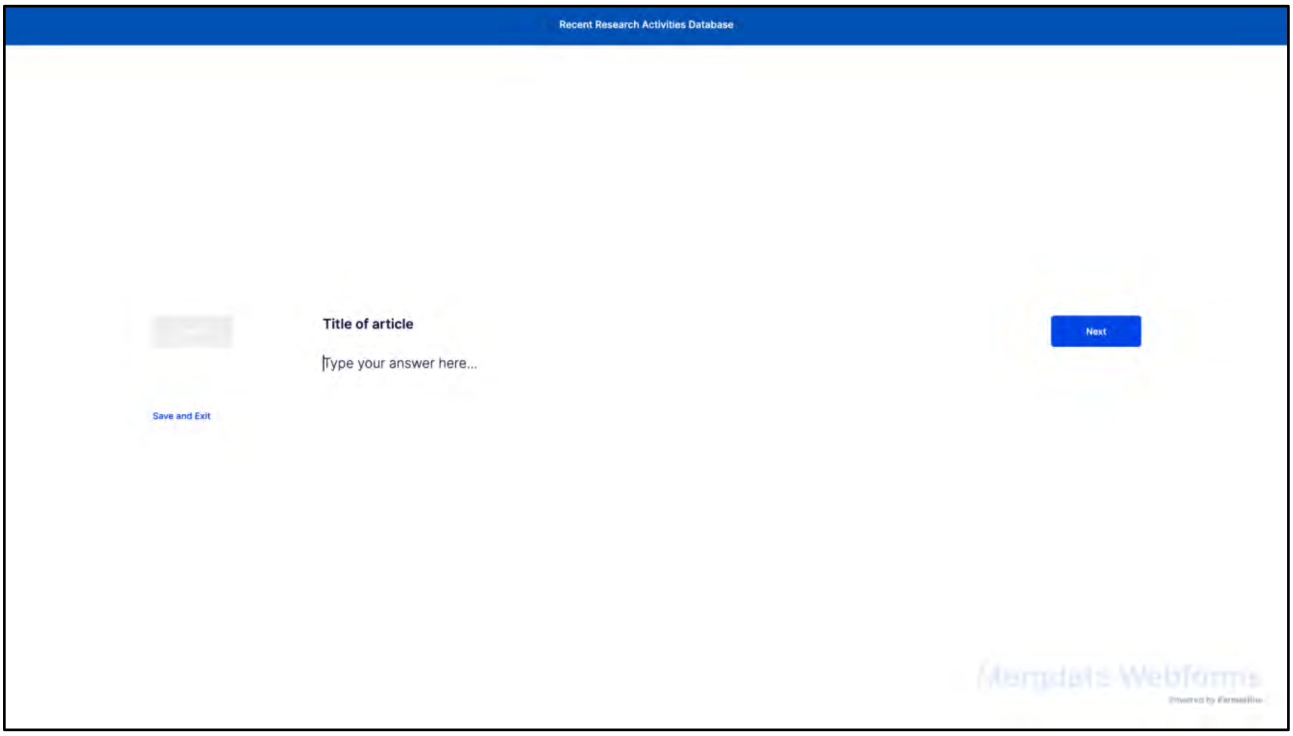


Link to Business Research Database : [Business Research Database]

Recent Research Activities Database

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 861924

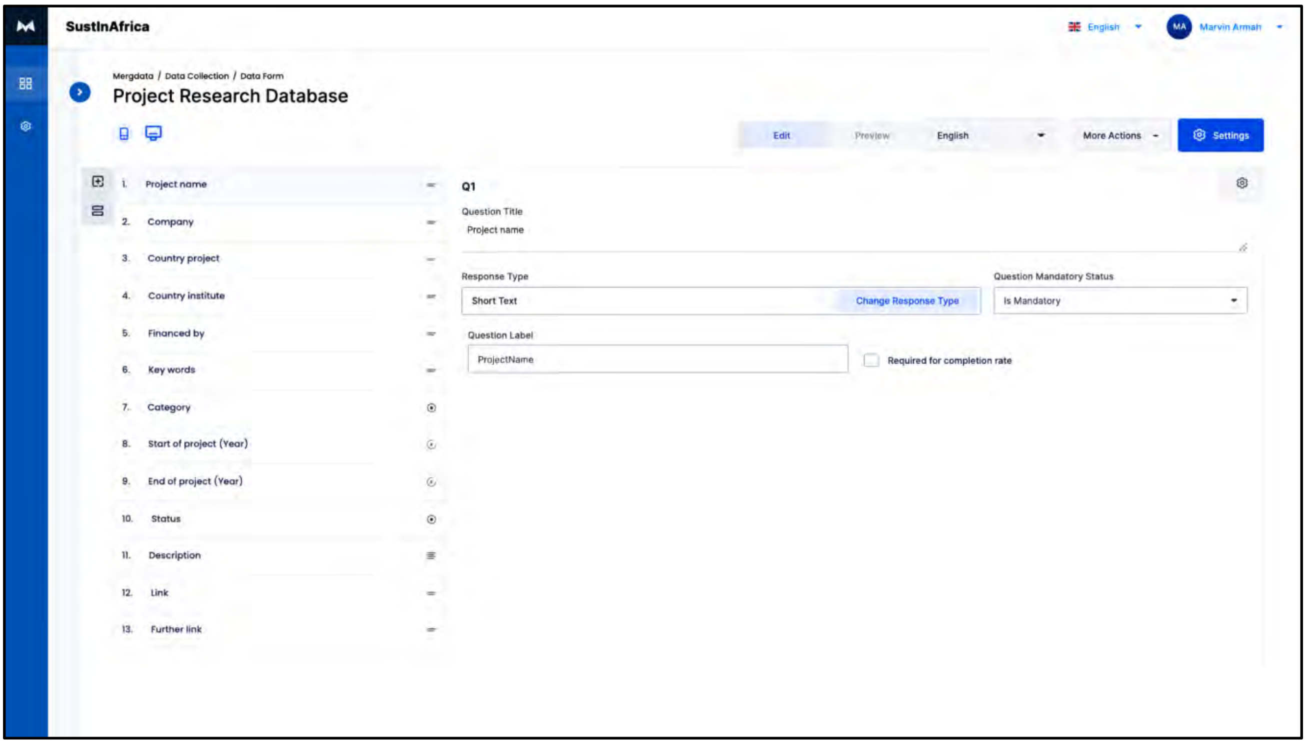




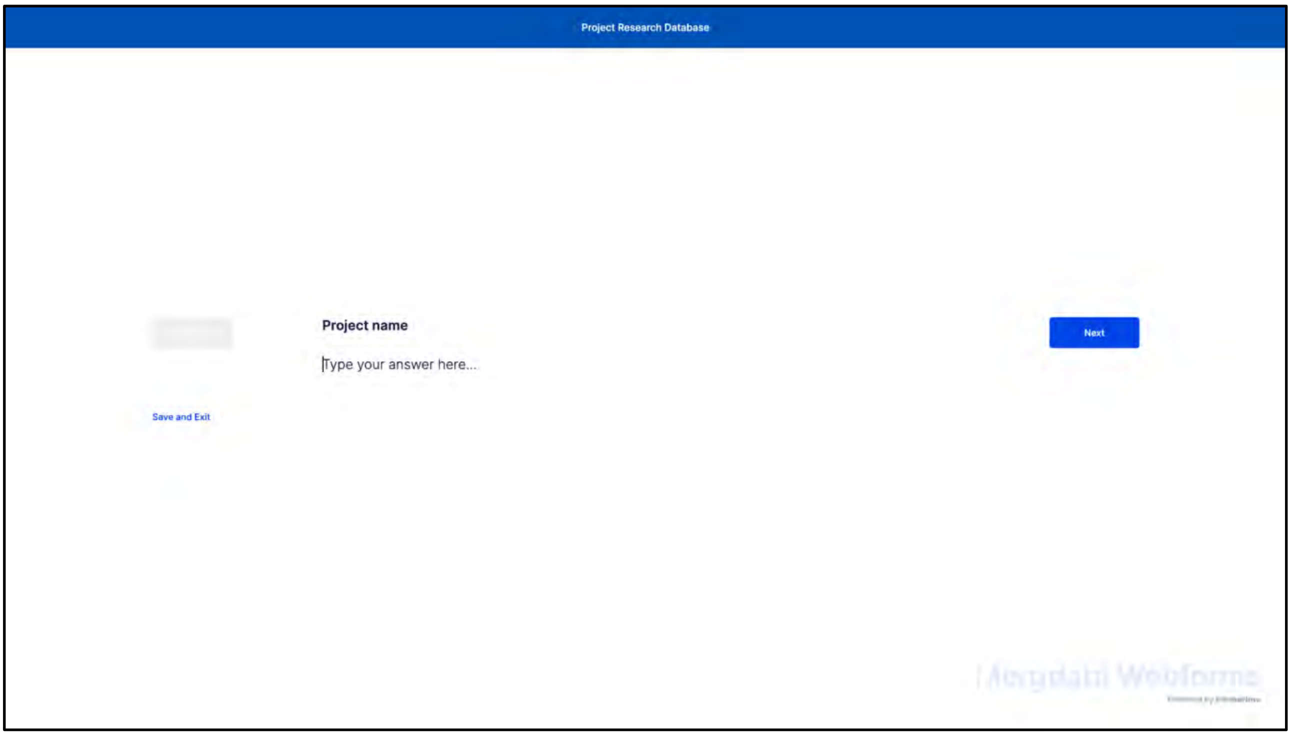
Link to Recent Research Activities Database : [Recent Research Activities Database]

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 861924

Project Research Database



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 861924



Link to Project Research Database: [Project Research Database]

Annex 4: Excel form used to introduce data and upload it to Mergdata

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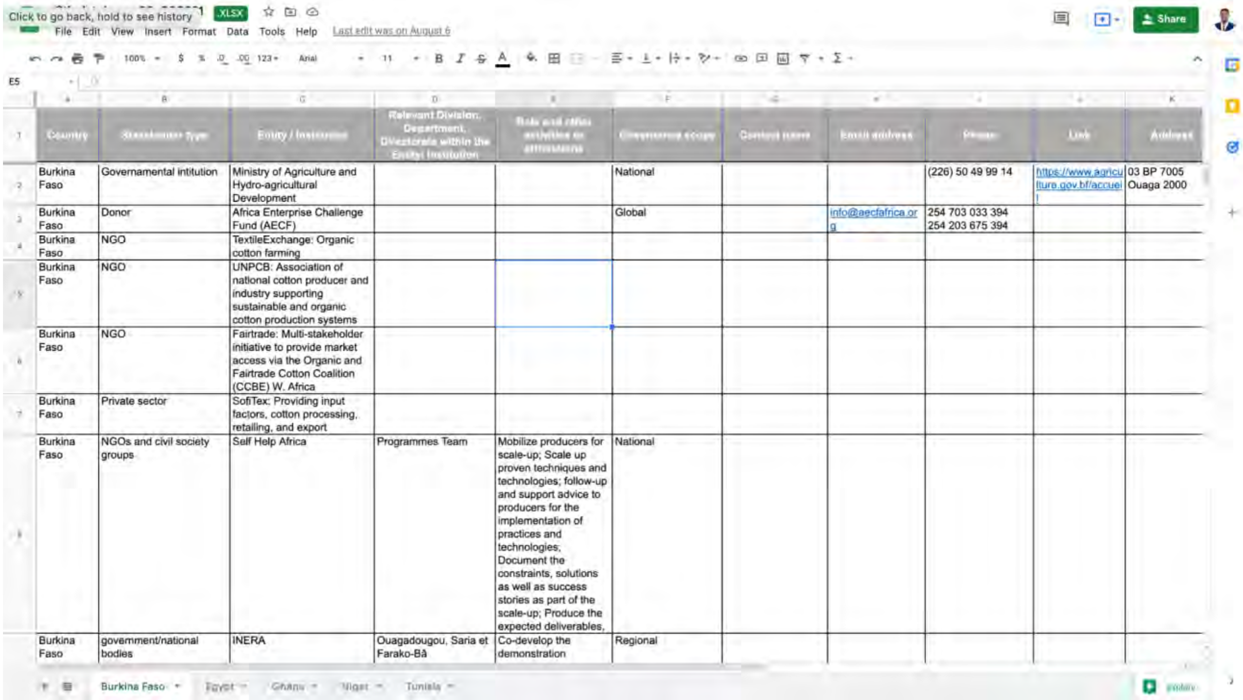
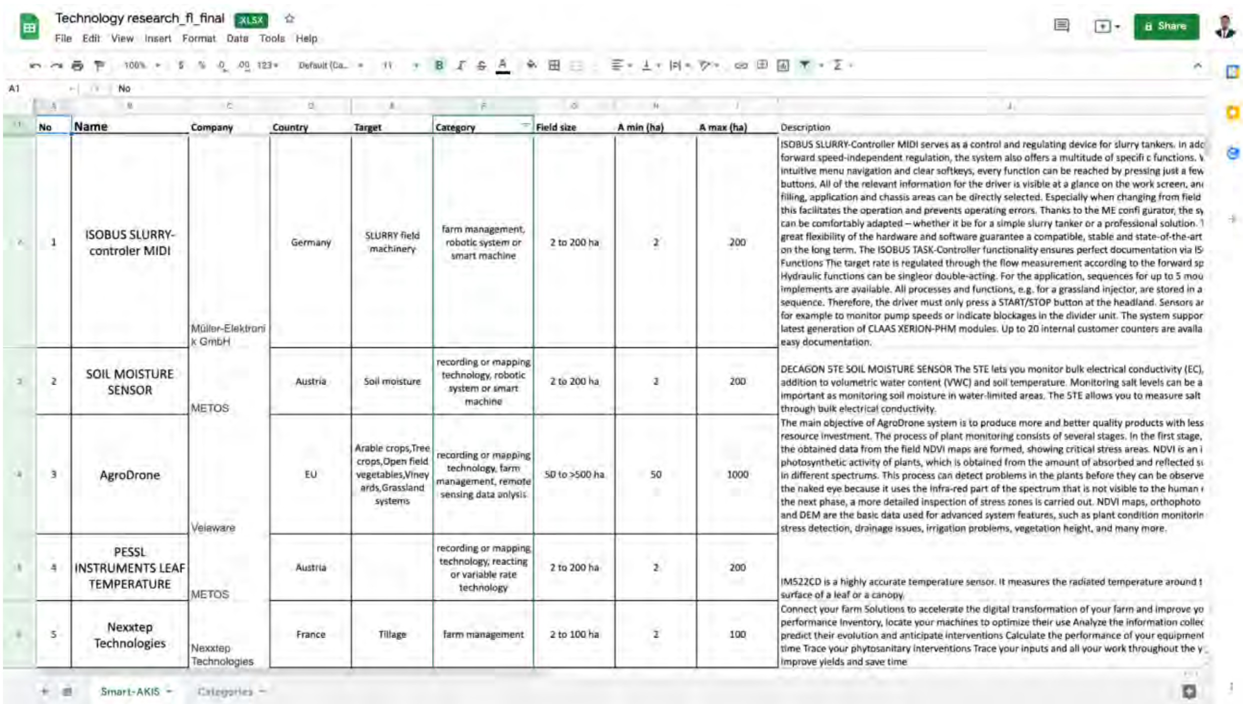
research and innovation programme under grant agreement N° 861924



Country	Stakeholder type	Entity / Institution	Relevant Division, Department, Directorate within the Entity/ Institution	Role and other activities or attributions	Geographical scope	Contact name	Email address	Phone	Link	Address
Burkina Faso	Governamental intitution	Ministry of Agriculture and Hydro-agricultural Development			National			(226) 50 49 99 14	https://www.agriculture.gov.bf/accueil	03 BP 7005 Ouaga 2000
Burkina Faso	Donor	Africa Enterprise Challenge Fund (AECF)			Global		info@aecfafrica.org	254 703 033 394 254 203 675 394		
Burkina Faso	NGO	TextileExchange: Organic cotton farming								
Burkina Faso	NGO	UNPCB: Association of national cotton producer and industry supporting sustainable and organic cotton production systems								
Burkina Faso	NGO	Fairtrade: Multi-stakeholder initiative to provide market access via the Organic and Fairtrade Cotton Coalition (CCBE) W. Africa								
Burkina Faso	Private sector	SofiTex: Providing input factors, cotton processing, retailing, and export								
Burkina Faso	NGOs and civil society groups	Self Help Africa	Programmes Team	Mobilize producers for scale-up; Scale up proven techniques and technologies; follow-up and support advice to producers for the implementation of practices and technologies; Document the constraints, solutions as well as success stories as part of the scale-up; Produce the expected deliverables,	National					
Burkina Faso	government/national bodies	INERA	Ouagadougou, Saria et Farako-Bâ	Co-develop the demonstration	Regional					



Technology research_fl_final

No	Name	Company	Country	Target	Category	Field size	A min (ha)	A max (ha)	Description
1	ISOBUS SLURRY-controler MIDI	Müller-Elektronik GmbH	Germany	SLURRY field machinery	farm management, robotic system or smart machine	2 to 200 ha	2	200	ISOBUS SLURRY-Controller MIDI serves as a control and regulating device for slurry tankers. In adc forward speed-independent regulation, the system also offers a multitude of specifi c functions. V intuitive menu navigation and clear softkeys, every function can be reached by pressing just a few buttons. All of the relevant information for the driver is visible at a glance on the work screen, an filling, application and chassis areas can be directly selected. Especially when changing from field this facilitates the operation and prevents operating errors. Thanks to the ME confi gurator, the sy can be comfortably adapted – whether it be for a simple slurry tanker or a professional solution. T great flexibility of the hardware and software guarantee a compatible, stable and state-of-the-art on the long term. The ISOBUS TASK-Controller functionality ensures perfect documentation via IS Functions The target rate is regulated through the flow measurement according to the forward sp Hydraulic functions can be singleor double-acting. For the application, sequences for up to 5 mou implements are available. All processes and functions, e.g. for a grassland injector, are stored in a sequence. Therefore, the driver must only press a START/STOP button at the headland. Sensors ar for example to monitor pump speeds or indicate blockages in the divider unit. The system suppor latest generation of CLAAS XERION-PHM modules. Up to 20 internal customer counters are availa easy documentation.
2	SOIL MOISTURE SENSOR	METOS	Austria	Soil moisture	recording or mapping technology, robotic system or smart machine	2 to 200 ha	2	200	DECAGON 5TE SOIL MOISTURE SENSOR The 5TE lets you monitor bulk electrical conductivity (EC), addition to volumetric water content (VWC) and soil temperature. Monitoring salt levels can be a important as monitoring soil moisture in water-limited areas. The 5TE allows you to measure salt through bulk electrical conductivity.
3	AgroDrone	Veleware	EU	Arable crops,Tree crops,Open field vegetables,Vineyards,Grassland systems	recording or mapping technology, farm management, remote sensing data anlysis	50 to >500 ha	50	1000	The main objective of AgroDrone system is to produce more and better quality products with less resource investment. The process of plant monitoring consists of several stages. In the first stage, the obtained data from the field NDVI maps are formed, showing critical stress areas. NDVI is an i photosynthetic activity of plants, which is obtained from the amount of absorbed and reflected su in different spectrums. This process can detect problems in the plants before they can be observe the naked eye because it uses the infra-red part of the spectrum that is not visible to the human e the next phase, a more detailed inspection of stress zones is carried out. NDVI maps, orthophoto and DEM are the basic data used for advanced system features, such as plant condition monitorin stress detection, drainage issues, irrigation problems, vegetation height, and many more.
4	PESSL INSTRUMENTS LEAF TEMPERATURE	METOS	Austria		recording or mapping technology, reacting or variable rate technology	2 to 200 ha	2	200	IMS22CD is a highly accurate temperature sensor. It measures the radiated temperature around t surface of a leaf or a canopy.
5	Nexxtep Technologies	Nexxtep Technologies	France	Tillage	farm management	2 to 100 ha	2	100	Connect your farm Solutions to accelerate the digital transformation of your farm and improve yo performance Inventory, locate your machines to optimize their use Analyze the information collec predict their evolution and anticipate interventions Calculate the performance of your equipment time Trace your phytosanitary interventions Trace your inputs and all your work throughout the y improve yields and save time

Smart-AKIS Categories

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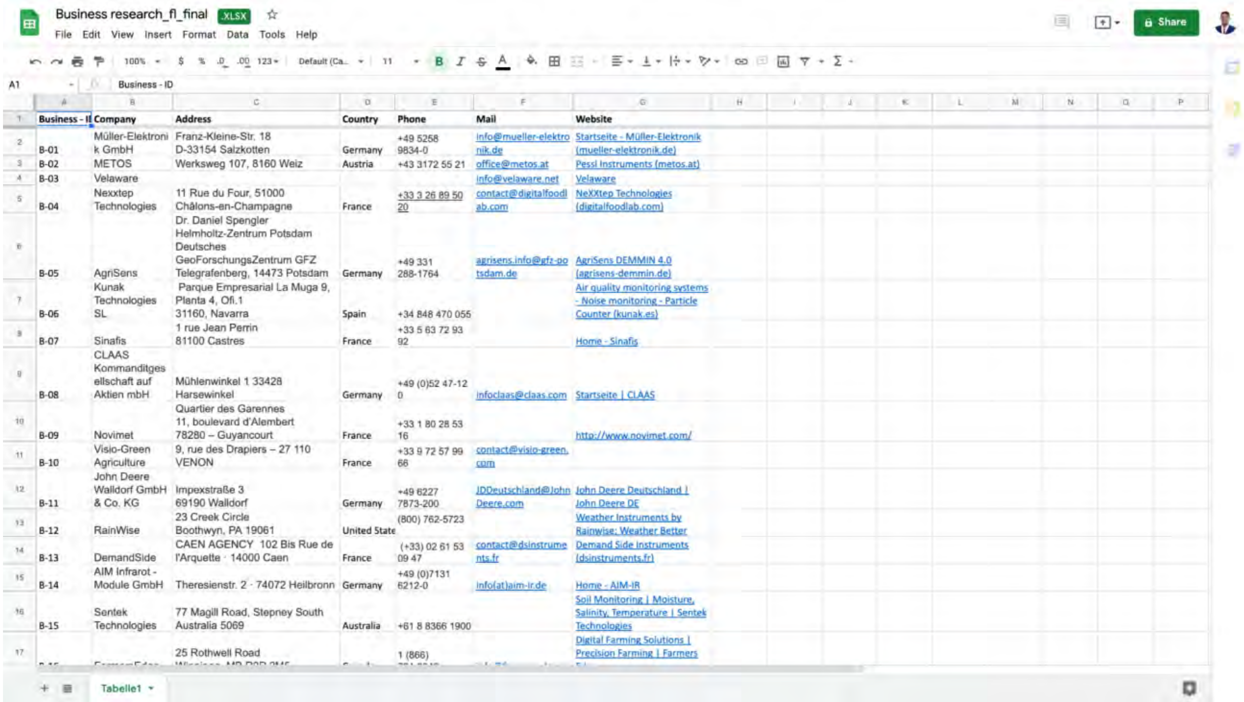
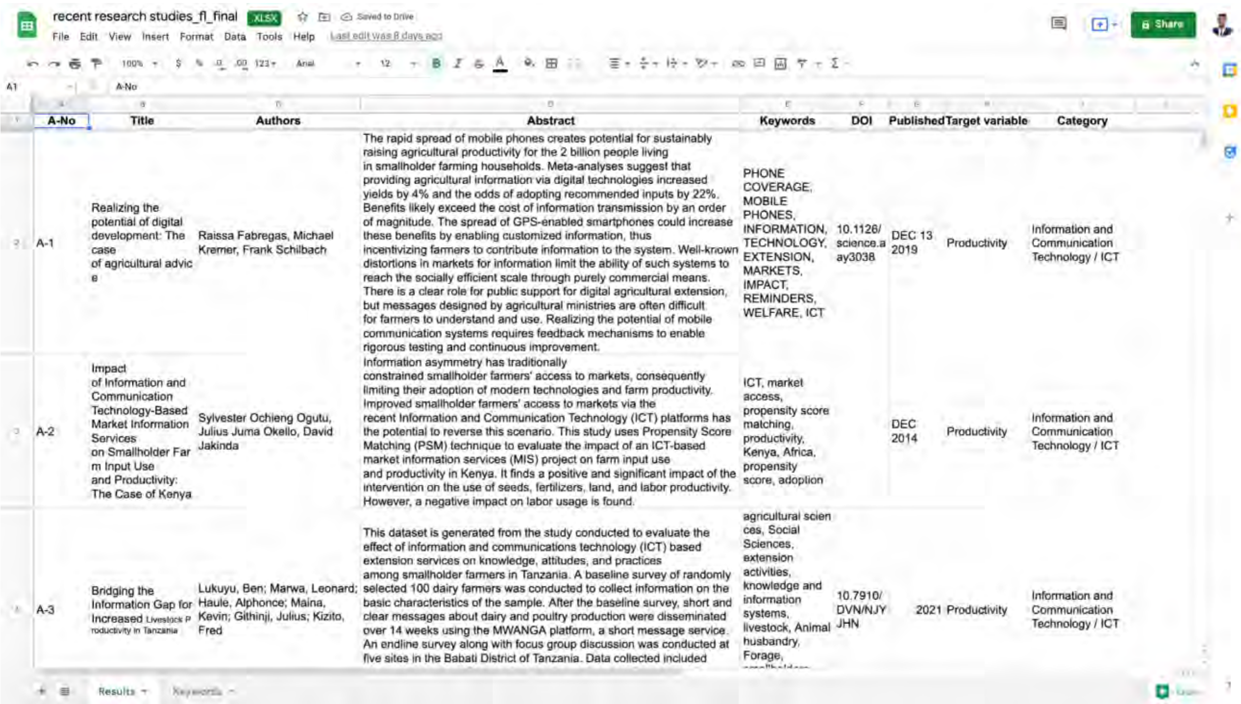


Business research_fl_final

Business - ID	Company	Address	Country	Phone	Mail	Website
B-01	Müller-Elektronik GmbH	Franz-Kleine-Str. 18 D-33154 Salzkotten	Germany	+49 5258 9834-0	info@mueller-elektronik.de	Startseite - Müller-Elektronik (mueller-elektronik.de)
B-02	METOS	Werksweg 107, 8160 Weiz	Austria	+43 3172 55 21	office@metos.at	Pessl Instruments (metos.at)
B-03	Velaware				info@velaware.net	Velaware
B-04	Nexxtep Technologies	11 Rue du Four, 51000 Châlons-en-Champagne	France	+33 3 26 89 50 20	contact@digitalfoodlab.com	NeXXtep Technologies (digitalfoodlab.com)
B-05	AgriSens	Dr. Daniel Spengler Helmholtz-Zentrum Potsdam Deutsches GeoForschungsZentrum GFZ Telegrafenberg, 14473 Potsdam	Germany	+49 331 288-1764	agrisens.info@gfz-potsdam.de	AgriSens DEMMIN 4.0 (agrisens-demmin.de)
B-06	Kunak Technologies SL	Parque Empresarial La Muga 9, Planta 4, Ofi.1 31160, Navarra	Spain	+34 848 470 055		Air quality monitoring systems - Noise monitoring - Particle Counter (kunak.es)
B-07	Sinafis	1 rue Jean Perrin 81100 Castres	France	+33 5 63 72 93 92		Home - Sinafis
B-08	CLAAS Kommanditgesellschaft auf Aktien mbH	Mühlenwinkel 1 33428 Harsewinkel	Germany	+49 (0)52 47-12 0	infoclaas@claas.com	Startseite | CLAAS
B-09	Novimet	Quartier des Garennes 11, boulevard d'Alembert 78280 – Guyancourt	France	+33 1 80 28 53 16		http://www.novimet.com/
B-10	Visio-Green Agriculture	9, rue des Drapiers – 27 110 VENON	France	+33 9 72 57 99 66	contact@visio-green.com	
B-11	John Deere Walldorf GmbH & Co. KG	Impexstraße 3 69190 Walldorf	Germany	+49 6227 7873-200	JDDeutschland@JohnDeere.com	John Deere Deutschland | John Deere DE
B-12	RainWise	23 Creek Circle Boothwyn, PA 19061	United State	(800) 762-5723		Weather Instruments by Rainwise: Weather Better
B-13	DemandSide	CAEN AGENCY 102 Bis Rue de l'Arquette · 14000 Caen	France	(+33) 02 61 53 09 47	contact@dsinstruments.fr	Demand Side Instruments (dsinstruments.fr)
B-14	AIM Infrarot - Module GmbH	Theresienstr. 2 · 74072 Heilbronn	Germany	+49 (0)7131 6212-0	info(at)aim-ir.de	Home - AIM-IR
B-15	Sentek Technologies	77 Magill Road, Stepney South Australia 5069	Australia	+61 8 8366 1900		Soil Monitoring | Moisture, Salinity, Temperature | Sentek Technologies
		25 Rothwell Road		1 (866)		Digital Farming Solutions | Precision Farming | Farmers

Tabelle1



recent research studies_fl_final

A-No	Title	Authors	Abstract	Keywords	DOI	Published	Target variable	Category
A-1	Realizing the potential of digital development: The case of agricultural advice	Raissa Fabregas, Michael Kremer, Frank Schilbach	The rapid spread of mobile phones creates potential for sustainably raising agricultural productivity for the 2 billion people living in smallholder farming households. Meta-analyses suggest that providing agricultural information via digital technologies increased yields by 4% and the odds of adopting recommended inputs by 22%. Benefits likely exceed the cost of information transmission by an order of magnitude. The spread of GPS-enabled smartphones could increase these benefits by enabling customized information, thus incentivizing farmers to contribute information to the system. Well-known distortions in markets for information limit the ability of such systems to reach the socially efficient scale through purely commercial means. There is a clear role for public support for digital agricultural extension, but messages designed by agricultural ministries are often difficult for farmers to understand and use. Realizing the potential of mobile communication systems requires feedback mechanisms to enable rigorous testing and continuous improvement.	PHONE COVERAGE, MOBILE PHONES, INFORMATION, TECHNOLOGY, EXTENSION, MARKETS, IMPACT, REMINDERS, WELFARE, ICT	10.1126/science.aay3038	DEC 13 2019	Productivity	Information and Communication Technology / ICT
A-2	Impact of Information and Communication Technology-Based Market Information Services on Smallholder Farm Input Use and Productivity: The Case of Kenya	Sylvester Ochieng Ogutu, Julius Juma Okello, David Jakinda	Information asymmetry has traditionally constrained smallholder farmers' access to markets, consequently limiting their adoption of modern technologies and farm productivity. Improved smallholder farmers' access to markets via the recent Information and Communication Technology (ICT) platforms has the potential to reverse this scenario. This study uses Propensity Score Matching (PSM) technique to evaluate the impact of an ICT-based market information services (MIS) project on farm input use and productivity in Kenya. It finds a positive and significant impact of the intervention on the use of seeds, fertilizers, land, and labor productivity. However, a negative impact on labor usage is found.	ICT, market access, propensity score matching, productivity, Kenya, Africa, propensity score, adoption		DEC 2014	Productivity	Information and Communication Technology / ICT
A-3	Bridging the Information Gap for Increased Livestock Productivity in Tanzania	Lukuyu, Ben; Marwa, Leonard; Haule, Alphonce; Maina, Kevin; Githinji, Julius; Kizito, Fred	This dataset is generated from the study conducted to evaluate the effect of information and communications technology (ICT) based extension services on knowledge, attitudes, and practices among smallholder farmers in Tanzania. A baseline survey of randomly selected 100 dairy farmers was conducted to collect information on the basic characteristics of the sample. After the baseline survey, short and clear messages about dairy and poultry production were disseminated over 14 weeks using the MWANGA platform, a short message service. An endline survey along with focus group discussion was conducted at five sites in the Babati District of Tanzania. Data collected included	agricultural sciences, Social Sciences, extension activities, knowledge and information systems, livestock, Animal husbandry, Forage,	10.7910/DVN/NJYJHN	2021	Productivity	Information and Communication Technology / ICT

Results

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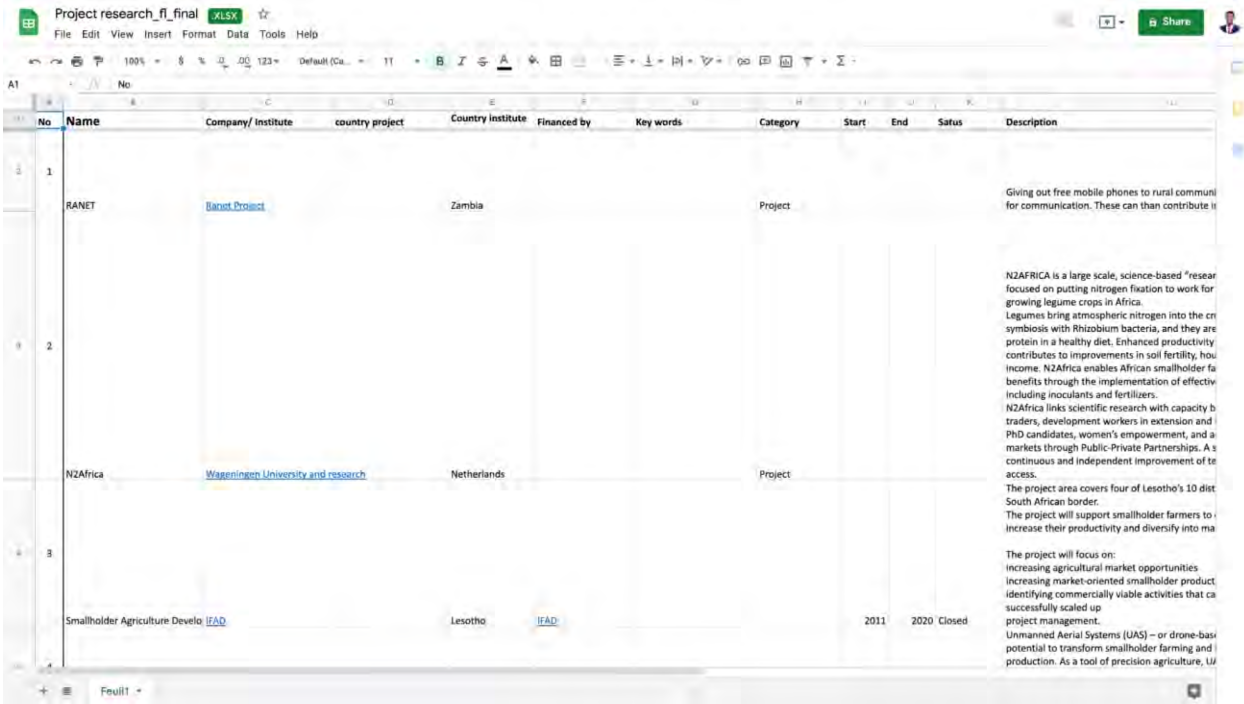

No	Name	Company/ Institute	country project	Country institute	Financed by	Key words	Category	Start	End	Satus	Description
1	RANET	Ranet Project		Zambia			Project				Giving out free mobile phones to rural communi for communication. These can than contribute i
2	N2Africa	Wageningen University and research		Netherlands			Project				N2AFRICA is a large scale, science-based "resear focused on putting nitrogen fixation to work for growing legume crops in Africa. Legumes bring atmospheric nitrogen into the cr symbiosis with Rhizobium bacteria, and they are protein in a healthy diet. Enhanced productivity contributes to improvements in soil fertility, hou income. N2Africa enables African smallholder fa benefits through the implementation of effectiv including inoculants and fertilizers. N2Africa links scientific research with capacity b traders, development workers in extension and PhD candidates, women's empowerment, and a markets through Public-Private Partnerships. A s continuous and independent improvement of te access.
3	Smallholder Agriculture Develo	IFAD		Lesotho	IFAD			2011	2020	Closed	The project area covers four of Lesotho's 10 dist South African border. The project will support smallholder farmers to increase their productivity and diversify into ma The project will focus on: increasing agricultural market opportunities increasing market-oriented smallholder product identifying commercially viable activities that ca successfully scaled up project management. Unmanned Aerial Systems (UAS) – or drone-bas potential to transform smallholder farming and production. As a tool of precision agriculture, UA
4											

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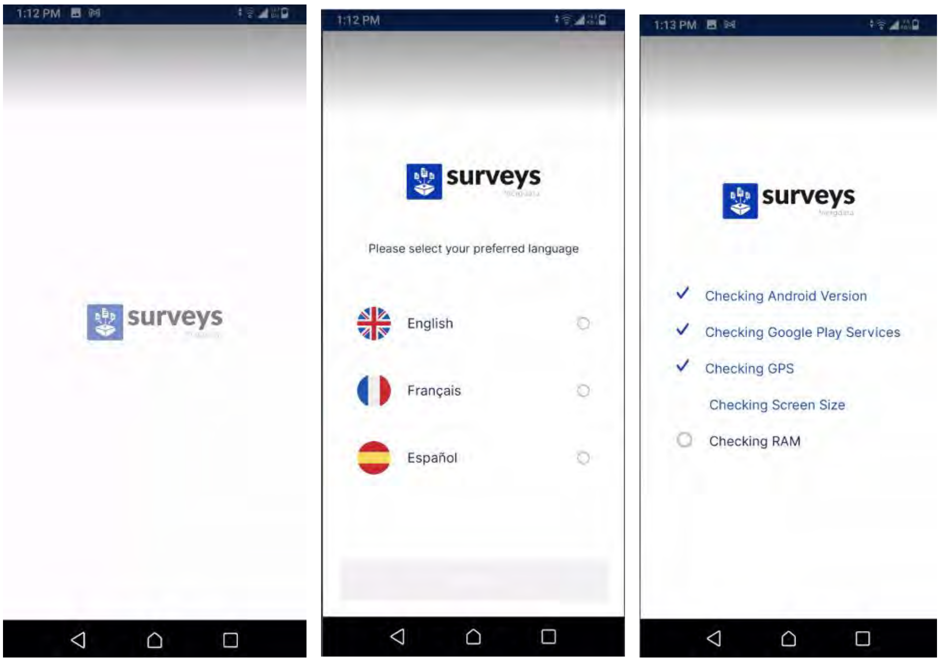
Annex 5: User Interface of Mergdata Android App



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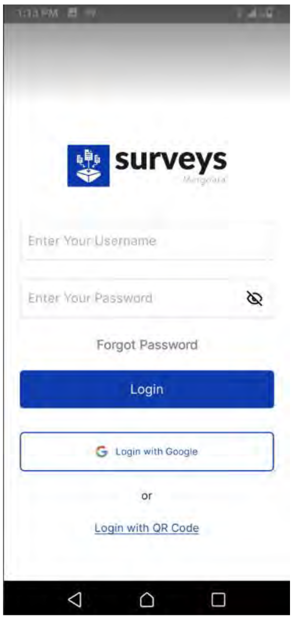

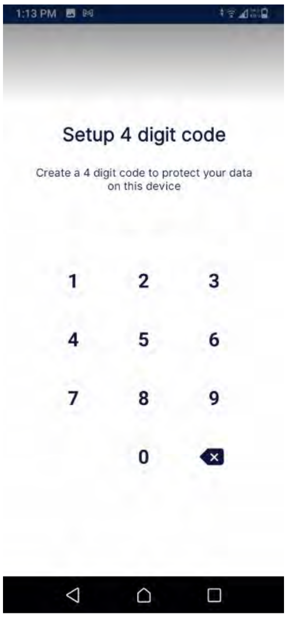

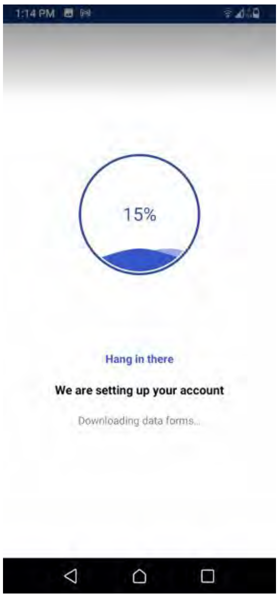

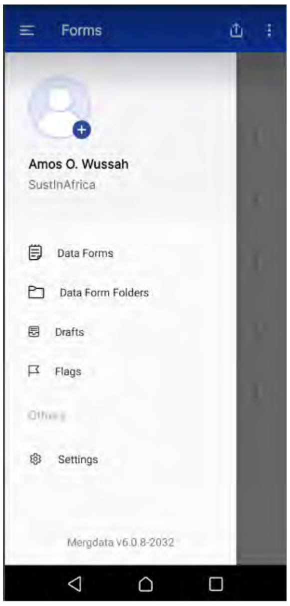

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