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ADOPTION OF ARTIFICIAL INTELLIGENCE BASED TECHNOLOGIES IN SUB-SAHARAN AFRICAN AGRICULTURE

Benedikt Reiger, BSc

Dissertation presented as partial requirement for obtaining the Master's degree in Information Management.

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by

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Dissertation presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Knowledge Management and Business Intelligence.

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Abstract

Sub-Saharan Africa (SSA) is currently facing numerous agriculture related challenges such as climate change, lacking infrastructure, and limited institutional as well as economic support. However, current research does not provide holistic solutions to this problem. This study aims to shed light on this topic through the development of a model that can be used to assess the solution potential as well as high-level implementation requirements of selected artificial intelligence (AI) based agriculture technologies in the context of SSA. To thoroughly develop the above-mentioned model a design science approach was followed. First an in depth (systematic) literature review was conducted where the agriculture related challenges in SSA and state-of-the-art AI-based agriculture technologies are detailed. This step was followed by the creation of a model that aims to find a nexus between the researched challenges and available technologies as potential solutions. Furthermore, the framework outlines context specific technology adoption requirements. Lastly, expert interviews were conducted to validate and revise the proposed model. The final framework clearly highlights the positive impact AI based technologies can have in SSA's agriculture and the basic conditions that need to be met to successfully implement them.

Keywords

Technology; Agriculture; Artificial Intelligence; Design Science; Sub-Saharan Africa

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List of Abbreviations and Acronyms

AgriTech	Agriculture Technology
AI	Artificial Intelligence
DSR	Design Science Research
IoT	Internet of Things
ML	Machine Learning
PA	Precision Agriculture
SSA	Sub-Saharan Africa
UA	Urban Agriculture
UAV	Unmanned Aerial Vehicles

1. Introduction

1.1. Background

Despite holding more than 60% of the world's uncultivated farmland, Africa continues to play a subordinate role when it comes to its worldwide food supply contribution. However, around two-thirds of Africa's population rely on agriculture to make a living. These, for the most part smallholder farmers produce about 90 percent of the food supply (Cornock, 2019). The conditions under which these farmers operate make them more vulnerable to agriculture related challenges than farmers in developed countries (Woetzel et al., 2020). For instance, it is estimated that 50 to 85 percent of farming work in Africa is completed by hand without the support of machines and 95 percent of its livestock as well as cropping systems are purely rainfed (Malabo Montpellier Panel, 2018).

Among the many challenges, that particularly smallholder farmers face, the climate change is one of the biggest (Pereira, 2017). Crop and livestock yields are becoming more volatile due to an increasing climate variability with more frequent and extreme weather events driven by rising temperatures and shifting rainfall trends. Moreover, the quantity and quality of forage, water scarcity, and extreme weather events can pose a risk to the health of livestock. Additionally, the development of diseases and pest resilience of crops and livestock can be negatively affected by climate change (Woetzel et al., 2020).

On top of climate change, population related issues exist that affect the development of African agriculture. By 2050 worldwide nine billion people will need to be fed which puts pressure on Africa's contribution to global food production (Solidaridad, 2020). This pressure is further increased by the fact that SSA's population is expected to more than double by 2050 which will continue to enlarge the current gap between food supply and demand (Van Ittersum et al., 2016). In fact, Africa's food production needs to triple to close this gap (Dupoux & Zrikem, 2017). However, an increase in population size tends to result in over cultivation which harms land productivity (Epule et al., 2015).

Lastly, Africa's agriculture industry suffers from limited economic and institutional support (Sultan & Gaetani, 2016). This limited support is also reflected in the lack of funding that goes to the agriculture sector of Africa. Consequently, Africa has been unable to adopt modern agronomy technologies in contrast to, for instance, India's "green revolution" (Dupoux & Zrikem, 2017).

The combination of the above outlined agriculture related challenges can be detrimental to the African continent and not only result in serious food crises but also force refugee movements (Epule et al., 2015). However, if the challenges are overcome, Africa has the potential to double or even triple its food production (Goedde et al., 2019). Agriculture not only drives food security but also creates employment opportunities as well as higher wages (Machethe, 2004). Additionally, the largest part of Africa’s population is working in the agriculture sector. Therefore, developing this industry is by many believed to be the most successful approach for reducing poverty and thus, improving living conditions in this region (Cornock, 2019).

1.2. Problem Identification

The question remains, how can the agriculture industry in African countries be developed to ensure productivity increase to guarantee food security as well as overall poverty reduction despite climate related challenges such as desertification, lack of water, or increasing climate variability and lacking institutional support (Routray et al., 2019; Sultan & Gaetani, 2016). The application of AI driven technologies across the African agriculture sector can be the key to increase the quantity and quality of crop and livestock yields while ensuring the sustainable use of critical resources (Dharmaraj & Vijayanand, 2018). Various AI-based technologies exist to support, among others, crop, soil, weed, and disease management (Bannerjee et al., 2018). For instance, one of the most popular underlying techniques used for soil management is artificial neural networks (ANN), which mimics the workings of a human brain (Eli-Chukwu, 2019; Jha et al., 2019).

Despite conducted research on AI-enabled technologies in agriculture, such as the work done by Eli-Chukwu (2019) regarding, among others, the applications of ANNs in soil management, current literature fails to put these techniques in the context of African or, more notably, SSA’s agriculture. Instead, they tend to discuss the technologies as if they would be implemented in a vacuum. Authors that do tailor their research to specific regions, as exemplified by papers from Mondal and Basu (2009), Say et al. (2018), or Routray et al. (2019) usually focus on China, India, or developing countries in general. Furthermore, these papers tend to lack focus on the AI-enabled technologies but rather discuss precision agriculture technologies in general. Moreover, they stress the adoption rates that have been achieved in certain regions to prove the respective impact of new technologies in agriculture opposed to detailing adoption scenarios. However, this general approach comes at the expense of detailing the technology adoption strategies with regards to resource constraints, such as data or infrastructure requirements. Yet, one needs to take these constraints into account to select the AI-based agricultural technologies that generate the most significant socio-economic benefit under the present regional conditions.

In conclusion, current literature lacks the combination of a regional focus on SSA, an analysis of AI-based technologies in agriculture, and the description of adoption requirements for successful technology implementation. Based on this research gap the following research question was inferred:

Can the adoption of AI based technologies solve sub-Saharan Africa's agricultural challenges?

1.3. Study Objectives

The aim of this paper consists in answering the above-mentioned research question through the development of a model that outlines which AI-based technologies for crop, soil, weed, and disease management are appropriate to be applied in SSA's challenging agriculture industry. This includes the consideration of the overall impact and implementation requirements of the identified technologies. To achieve this goal, the following intermediate objectives were defined.

- Description of agriculture landscape in SSA
- Description of existing AI-based techniques in the agriculture industry
- Definition of nexus regarding how AI-based agriculture technologies can solve agriculture related challenges in Africa
- Development of agriculture technology adoption requirements.

1.4. Study Relevance and Importance

The African agriculture industry is currently facing several challenges from coping with climate change over rapid population growth to systematic underfunding (Dupoux & Zrikem, 2017; Epule et al., 2015; Peraira, 2017; Van Ittersum et al., 2016). Considering the high reliance of the African population on the agriculture sector (Cornock, 2019), all these factors have the potential to increase the already existing food supply and demand gap and at worst, lead to food crises triggering refugee movements (Epule et al., 2015; Van Ittersum et al., 2016). Consequently, it is of the utmost importance to not only shed light on the agricultural challenges that lie in the present and future but also propose practical solutions on how to solve them.

From a societal point of view understanding the impact as well as implementation requirements of AI-based agricultural techniques allows one to select and apply the right technology for the right scenario. This is critical to ensure that, for instance, the limited financial efforts of African farmers, are effectively and efficiently used (Sultan & Gaetani, 2016). In turn, the right technologies can help African agriculture to sustainably evolve in terms of total production output and technology advancement like India's "green revolution" despite prevailing challenges such as climate change

(Dupoux & Zrikem, 2017). Lastly, developing the agricultural sector does not only imply a positive impact on food security but it can also serve as a pathway to effectively reduce poverty overall through the creation of employment opportunities and an increase in real wages (Machethe, 2004; Tam et al., 2014).

Considering the lack of current literature as previously outlined, conducting research focused on AI-based agriculture technologies will sharpen the line that distinguishes between agriculture technologies that in fact include “intelligent” components and the ones that do not. Moreover, focusing on a region that has received relatively little attention in scientific studies, will help to close the geographic research gap which the African agriculture can be regarded as. Finally, looking at new technologies, such as AI-based agriculture techniques, in a practical context and studying the adoption requirements and implementation practices, opposed to analysing adoption rates, is necessary to ensure that scientific studies can become effective drivers for technology implementation.

2. Methodology

Considering the final output of this paper is a novel theoretical model with practical applicability, the design science research (DSR) approach, as proposed by Hevner et al. (2004), was chosen. A detailed description of DSR and its application is outlined below.

2.1. Design Science Research

In essence, the design science paradigm constitutes a problem-solving framework with the goal of developing innovative artifacts to solve an existing specified issue. This artifact needs to be purposeful and new in the sense that it must be useful in solving an unsolved problem or solving a problem in a more efficient or effective way (Hevner et al., 2004). Generally, anything artificially created, which is advancing the status quo by solving problems as described before, can be considered an artifact (Simon, 1996). The development of these artifacts is based on kernel theories, which are being challenged and adjusted with the use of the researcher's intuition, experience, ingenuity, and critical thinking skills (Markus, Majchrzak, & Gasser, 2002; Walls, Widmeyer, & El Sawy, 1992). The framework that leads to the creation of an artifact, as outlined in the figure below, consist of an iterative process with three cycles which can mutually reinforce each other.

In the first so-called relevance cycle, the context of the problem, which serves as the starting point of the DSR approach, is defined. This problem space is referred to as environment, which is composed of the people, organizations, and respective existing or planned technologies. This environment comprises the objectives, tasks, issues, and opportunities that define business needs depending on the perception of the people within the organisation. These perceptions are shaped differently when considering the roles, capabilities, and characteristics of people. Furthermore, the business needs are evaluated accounting for the organization's strategies, structure, culture, as well as processes and placed with respect to existing technology infrastructure, applications, communication architectures, and development capabilities. By confirming that all research activities are conducted with the business need in mind research relevance is ensured (Hevner et al., 2004). This cycle is essentially aimed at identifying the relevant success criteria against which the performance of the artifact can be evaluated.

The second so-called rigor cycle is founded on the knowledge base, which consists of foundations in the form of theories, frameworks, instruments, constructs, models, methods, and instantiations as well as methodologies. While the foundational inputs are used during the develop/build phase, the methodologies consist of guidelines applied in the justify/evaluate phase.

The combination of correctly using foundations and methodologies results in rigor (Hevner et al., 2004).

The last phase of the DSR approach consists of the design cycle. In this phase the artifact is developed/built and afterwards justified/evaluated. The criteria the artifact is justified/evaluated against are based on the environment and in case it does not meet these criteria the artifact is refined. On the other hand, if the artifact does meet the justification/evaluation criteria it can be applied in practice and the gained knowledge can be used to enlarge the existing knowledge base (Hevner et al., 2004).

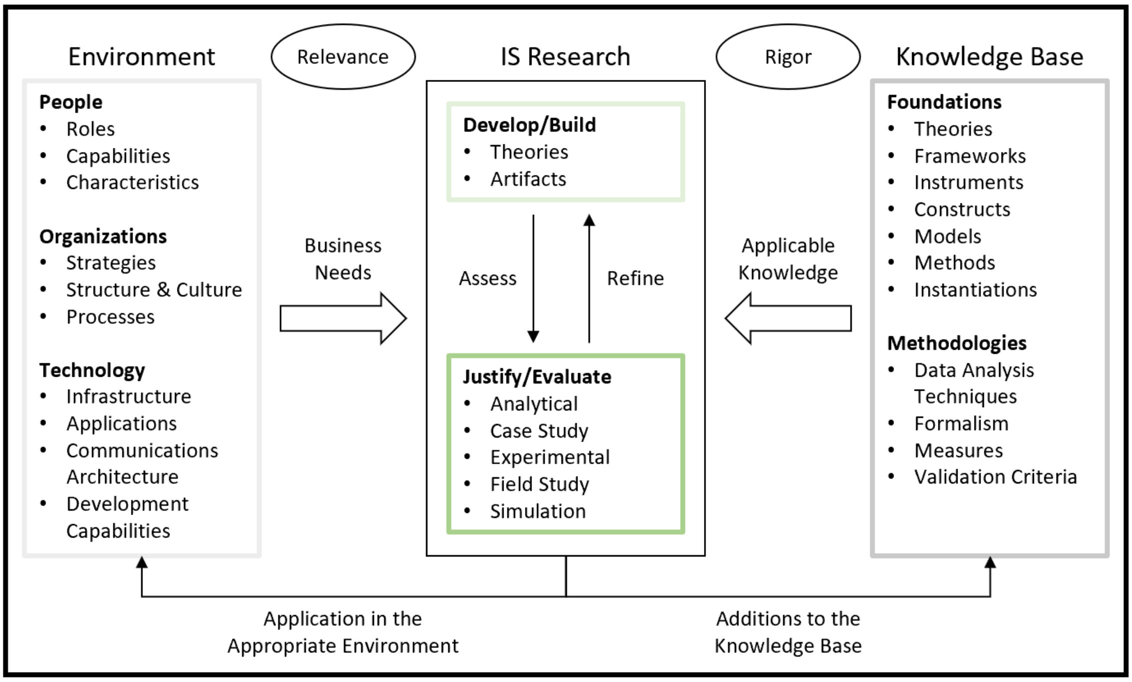


Figure 1 – Design Science Framework by Hevner et al. (2004)

2.2. Research Strategy

In this paper the framework by Hevner et al. (2004) is applied in the following way:

- **Environment**
  - During the environment phase the present agricultural challenges and goals are outlined. This is done in the context of farmers in SSA to ensure the specificity of the established problem space and, consequently, business needs. Furthermore, the status quo regarding existing AgriTech methods in SSA is analysed. This phase is primarily based on literature review.

- **Knowledge Base**
    - The knowledge base phase consists of the analysis of previous research conducted in the space of agriculture technologies. More precisely, theories about the impact of AI based AgriTech and instantiations about AI based AgriTech are studied. Furthermore, frameworks that try to link technologies with agricultural challenges are analysed. This phase is primarily based on a systematic literature review.
- **Develop/Build**
    - In the develop/build phase the insights from the environment and knowledge base are combined. Consequently, a model is created that aims to solve current agricultural challenges in the light of SSA's farmers with state-of-the-art AI based technologies including the consideration of adoption requirements.
- **Justify/Evaluate**
    - To effectively validate the in the previous stage developed model, numerous qualitative expert interviews are conducted. Through the input of the respective field experts, the created model can potentially be adjusted in an iterative manner.

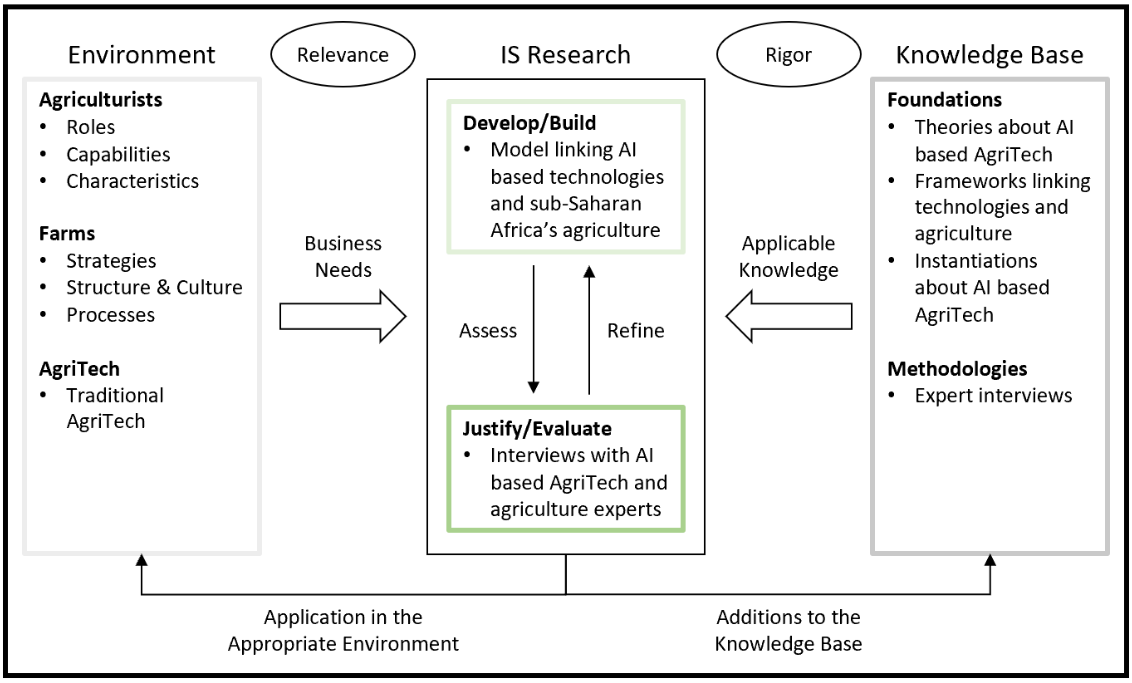


Figure 2 – Design Science Framework by Hevner et al. (2004) adjusted

3. Literature Review – Relevance Cycle

To get a thorough understanding how SSA's agriculture can benefit from AI based technologies it is necessary to comprehend the most pressing problems related to agriculture in the context of SSA. Developing this understanding requires a review of the past and current developments in SSA's agriculture landscape. Furthermore, the detailing of currently in SSA applied AgriTech is required. This will allow one to better draw the connection which and how AI based AgriTech can be used to address the present agricultural challenges in an efficient and effective manner.

3.1. Agriculture Definition

Before diving into the details of SSA's agriculture it is important to define agriculture. According to Harris and Fuller (2014) agriculture encompasses all activities through which crops and livestock provide food and other products to the world's population. These activities include cultivation, domestication, horticulture, arboriculture, vegeculture, and ways of livestock management like mixed crop-livestock farming, pastoralism, and transhumance. This definition already extends the literal meaning of the Latin word *agricultura* which is composed of the words *ager* (field) and *colo* (cultivate). On the other hand, Offutt (2002) offers a different way of defining agriculture by claiming that the definition of agriculture depends on the societal question one tries to answer. For instance, if the issue of food security is the question, then only heavy contributors to the food production would be included in the agriculture definition but not all units that conduct agricultural activities according to Harris and Fuller (2014). For this paper, the definition by Harris and Fuller (2014) is followed.

3.2. Agriculture in Sub-Saharan Africa

3.2.1. Overview

With more than 60 percent of the labour force being employed in agriculture, this sector has been of critical importance for the development of the African continent (Awotide et al., 2016). Despite this significance, SSA's agriculture sector has received little attention by politicians or investors in the past (Pereira, 2017). Unsurprisingly, according to Salami et al. (2010) the agriculture landscape in SSA used to be growing only marginally, showed low factor productivity, and insufficient trade activity. However, the authors state that towards the end of the last quarter of the 20th century, macroeconomic, sectoral, and institutional reforms with the goal of boosting economic growth, food security, and poverty alleviation took place in the region. SSA since boasts the fastest growth in agriculture out of all developing regions (Livingstone et al., 2011) but the high growth rate is to a large extent only the result of regions recovering from their extremely poor performance of the 1980s (Pereira, 2017). Additionally, Livingstone et al. (2011) point out that in contrast to other regions, the growth that is taking place is mostly driven by expansion of land cultivation opposed to an increase in land productivity. The reason for this is the high cost of capital needed to develop the agriculture industry versus the low cost of land in SSA but this strategy might not be sufficient or sustainable to cope with SSA's agricultural challenges discussed later in this paper.

3.2.2. Smallholder

Within SSA's agriculture most of all farms can be considered smallholder farms which drive the agricultural production. According to Livingstone et al. (2011) up to 80% of all farms are smallholder farms accounting for up to 90% of the food production. Similarly, Gollin (2014) and Salami et al. (2010) claim that almost all people working in SSA's agriculture are employed by smallholder farms. Despite this common understanding of the smallholder's role in the region, nuanced differences in the definition and emphasized characteristics of smallholder farms exist. While Livingstone et al. (2011) consider the size of farmland as the determining factor, Salami et al. (2010) defines smallholder based on the agro-ecological zones a farm operates in, type and composition of farm portfolio, or agriculture-based revenue streams. According to Bosc et al. (2013) and Moyo (2016) an important characteristic that is typical for smallholder farms is their dependency on family labour. Most smallholder agriculture is done by families or groups of families and their members. Within the families especially women play an important role in smallholder agriculture with regards to production, processing, and marketing activities. In conclusion, farms operating on a small scale dominate the agriculture landscape in SSA, both in terms of number of people employed and production output.

3.2.3. Large-Scale Farming

Despite the predominant smallholder farms, large-scale farms do exist in the region as well. According to Smalley (2014) and Lay et al. (2021) the number of large-scale farms in SSA is in fact growing rapidly. However, as pointed out by Deininger and Byerlee (2010) as well as Smalley (2014), the sustainable establishment of large commercial farms has proven to be highly difficult. The complications faced by developers included, among others, labour shortages, local land grievances, and lacking infrastructure, all of which smallholder farmers seem to be less susceptible to. While one might expect that the competition of large-scale farms harms the performance of the overrepresented smallholder farms, a study by Lay et al. (2021) provides evidence that the yield of smallholders near large-scale farms increased. This increase was likely driven by technology spillover effects according to Lay et al. (2021). Therefore, despite the currently still limited impact on SSA's total agriculture sector, large-scale farms can play an important role for the development of the industry in the region.

3.2.4. Urban Agriculture

In addition to the large-scale and smallholder farms, which can be assumed to exist mostly in rural areas, urban agriculture (UA) is getting more traction in SSA. UA can have many forms and may include backyard gardening or livestock farming in urban areas (Drechsel & Dongus, 2010). According to Davies et al. (2021) as well as Drechsel and Dongus (2010) the UA trend is driven by an increasing urbanization. It is estimated that 50% of Africa's population will live in urban areas by 2030 (Drechsel & Dongus, 2010). As a response to the rising demand for food in urban areas resulting from an increasing number of people living in this area, UA emerges. Consequently, the goal of UA is, among others, to improve food security. However, authors are uncertain to which extent UA contributes to food security. On the one hand older studies such as the ones by Lee-Smith (2010) and Cofie et al. (2003) stress how UA impacts food security and poverty reduction. On the other hand, Davies et al. (2021) point out that the relative impact of UA is small as most residents of urban areas prefer to rely on food purchases if food markets are within reach. Therefore, urban agriculture in SSA seems to be a solution for people with restricted access to food vendors but not a strategy to improve food security for the wider population.

3.3. AgriTech in Sub-Saharan Africa

The development of the agricultural sector in SSA in terms of production output has been mostly driven by expansion of farming land (Livingstone et al., 2011). This implies the continuation of traditional agricultural methods, which are characterised by, among others, manual labour, a lack of irrigation systems, and low crop variety. In fact, Africa currently hosts the worst mechanized agricultural sector in the world. Farmers in other developing regions have 10 times as many mechanized tools as African farmers. Up 50 to 85 percent of farming is done by hand with the use of tools like machetes, axes, or drills. About one quarter of power for farming stems from animal-powered machines, which in contrast to human-powered machinery increase production and processing levels significantly (Malabo Montpellier Panel, 2018).

According to Kassie et al. (2011) agricultural growth to ensure food security and poverty alleviation should not be the result of expanding cultivation areas but instead stem from a significant increase in land productivity driven by technology adoption. Developed countries, such as the United States, have started to adopt, for instance, precision agriculture (PA), which concerns the management of agricultural inputs by applying, among others, soil mapping, yield monitoring, or autonomous vehicles with the goal to improve land productivity. However, PA technologies are basically non-existent in SSA apart from South Africa where a limited number of farmers already use these technologies (Routray et al., 2019; Say et al., 2018). In other countries within SSA, such as Nigeria, Ethiopia, or Kenya PA is only applied by very few wealthy farmers and thus, still in a nascent phase (Routray et al., 2019).

3.4. Agriculture Related Challenges

Related to SSA's unique agriculture farmers still face an array of challenges. In the following part these are thoroughly outlined based on relevant studies and current research.

3.4.1. Climate

The change in climate and increasing variability are some of the biggest challenges for the agricultural development in SSA. The region is especially prone to climate related challenges due to SSA's rainfed dependent agriculture system and limited development with the majority of farmers being smallholders lacking necessary resources and appropriate infrastructure (Pereira et al., 2017; Zougmoré et al., 2018).

While the precise rate at which temperatures are expected to increase in SSA is unclear a scientific consensus that temperatures will rise significantly by 2050 exist according to Juana et al. (2013), Pereira et al. (2017), Thornton et al. (2011), and Zougmoré et al. (2018). Especially crop production yields will suffer from a warmer climate. However, the effect depends on the type of crop. Generally, maize production systems in SSA, which can be found for instance in South Africa and Zimbabwe, are less resilient to temperature increases (Pereira et al., 2017; Zougmoré et al., 2 018). Additionally, crop pests can spread into previously cooler regions. This would pose a threat to, for instance, coffee and banana production in countries like Ethiopia, Uganda, or Angola (Pereira et al., 2017). The increase in temperatures also further promotes the likelihood of droughts, which poses a threat to almost all agricultural activities in SSA since they rely nearly exclusively on rainfall and have no viable alternative irrigation system in place to cope with extended drought seasons (Besada & Werner, 2015; Juana et al., 2013).

In contrast to the trend of increasing temperatures, the projections regarding precipitation are more uncertain. According to Zougmoré et al. (2018) a decrease in overall rainfall in SSA is expected, while regional differences remain. Pereira et al. (2017) point out that especially the eastern region of SSA will experience a wetter future climate with more intense rainfall. In areas like Ethiopia but also western Africa no clarity over the magnitude or even direction of precipitation exists (Pereira et al., 2017). This lack of predictiveness highlights the increasing climate variability. Due to the changing rainfall trends extreme weather events, such as floods or droughts, become a bigger challenge for farmers in SSA as their intensity and frequency is expected to increase. With more climate variability the habitat for weeds can increase too, which can result in decreasing crop yields (Pereira et al., 2017).

3.4.2. Demography

With an expected growth in population size in SSA by the factor 2.5 until 2050, the demand for food such as cereals will triple according to Van Ittersum et al. (2016). This increasing gap between food demand and supply puts additional pressure on a region where at least one in four people is undernourished and food insecurity continues to be on the agenda (Besada & Werner, 2015). This increase in the number of people also results in an increase in population density across SSA, which requires a paradigm shift within SSA's agriculture system. While low population density regions can afford low land productivity, high population density areas cannot. In order to feed people in these regions, simply cultivating more land to push food production is not a feasible option and instead land productivity needs to be increased (Mellor, 2014). However, most of SSA's past agricultural growth has been driven by expansion of farming land (Livingstone et al., 2011).

3.4.3. Infrastructure

One of the main challenges in SSA is its poor infrastructure which constitutes a significant barrier to agricultural activities. According to Jayne et al. (2010), Mellor (2014), and Salami et al. (2010) the road and rail network is considerably underdeveloped. However, these networks are vital to ensure efficient transportation and keep the associated costs down to remain competitive in the food market (Jayne et al., 2010). Moreover, Mellor (2014) points out that rural electrification is lacking in SSA, which is necessary for most forms of modern agriculture. The need for affordable electricity is also highlighted by Salami et al. (2010) who considers it a barrier to investments in cooled storage facilities as well as irrigation and processing systems. Consequently, not only logistical constraint but also barriers to trade activities arise. The importance of a working infrastructure system for the agricultural sector becomes also clear when looking at the green revolution that took place in Asia. It is said that one of the key factors why the transformation of the agricultural sector has been significantly more successful in Asia versus Africa is its superior infrastructure with an intact road system and working electricity (Bachewe et al., 2017; Dawson et al., 2016).

3.4.4. Policies

Another issue that SSA is facing constitutes its poor policy and institutional support for the agriculture sector. According to Salami et al. (2010), in countries like Ethiopia or Kenya inappropriate policies are mostly related to land distribution and tenure, price regulatory frameworks, and marketing of agricultural commodities. Gollin (2014) stresses the negative development regarding to land distribution with African governments promoting land access for large-scale commercial farms at the expense of smallholders which make up the majority of SSA's farmers. Moreover, the poor institutional support is reflected in the insufficient knowledge about non-traditional agriculture techniques needed for mechanized forms of farming most smallholder in SSA have (Sims et al., 2016). Overall, policy constraints combined with the weak administrative and technical capacity of the ministries of agriculture make it extremely difficult to increase the productivity of SSA's agriculture sector (Salami et al., 2010).

3.4.5. Finances

As pointed out by Mellor (2014) the finance systems in African countries are insufficient. Again, especially the smallholder farmers receive a disproportional share of financial support, such as access to loans (Mellor, 2014; Salami et al., 2010). This is clearly detrimental to the development of SSA's agriculture considering the sector is mostly driven by smallholders and not better funded large-scale farmers. One of the main reasons for the lack of financial investments in SSA's agriculture is that its benefits only come to light in the long term. However, politically driven government bodies are mostly interested in short term payoffs as these tend to be more valued by society (Jayne et al., 2010).

In summary, the existing challenges within SSA's agriculture are manifold and related to the regions poor infrastructure, financial systems, and policy support. However, even more striking is probably the impact climate change and the development of the population has on the agriculture sector.

3.5. Agriculture Related Opportunities

Despite the many challenges that are related to SSA's agriculture landscape, opportunities with regards to SSA's agricultural production capacity and the sector's impact on poverty alleviation exist.

3.5.1. Resources

In addition to mineral resources, which have been recently discovered in East African countries according to Livingstone et al. (2011) and Salami et al. (2010), the most significant untapped resource in SSA is farming land. Even though Livingstone et al. (2011) point out that about half of SSA area is unsuitable for agricultural activities due to low fertility soil, the other half remains largely uncultivated. In fact, only ten percent of all arable land in Africa is currently used as farming land according to Kariuki (2011). With this abundance of unutilized land, SSA shows great potential for agricultural growth.

3.5.2. Poverty Reduction

With a rising global demand for food because of, among others, overall population growth (Salami et al., 2010), SSA can close the supply and demand food gap by exploiting its vast land resources as previously discussed. Developing its agricultural sector could not only contribute to global food security but also to local poverty alleviation. Many authors, such as Salami et al. (2010), Sims et al. (2016), or Sitko and Jayne (2019), claim that agricultural growth is one of the main drivers for poverty reduction in regions where most people work in the agriculture sector. Sitko and Jayne (2019) point out that a more developed agricultural sector results in higher levels of income and thus, increased purchasing power. As more money is put into the broader economy, employment opportunities outside of the agriculture sector are created, further promoting poverty alleviation.

4. Literature Review – Rigor Cycle

To be able to connect the latest AI based technologies in the agriculture industry with the pressing challenges SSA agriculture landscape is facing, one needs to develop an understanding for the technological background. In this section AI in general is discussed followed by an in-depth review of AI based technologies and applications in the agriculture sector.

4.1. Artificial Intelligence

4.1.1. Overview and Concepts

The term "artificial intelligence was first coined by John McCarthy in 1956 (Hussain, 2018). Today, this term is becoming more and more present in our lives and is mostly associated with some form of technological advancement (Martinez, 2019). According to Ongsulee (2017) AI is used when human-like cognitive functions such as "learning" or "problem solving" are mimicked by a machine. This definition is further extended by Pannu (2015) who states that AI is the study and development of intelligent machines that can also reason, gather knowledge, communicate, manipulate, and perceive objects. Furthermore, he points out that AI differs from psychology because it emphasizes computation, and it differs from computer science because it emphasizes perception, reasoning, and action. All of which makes machines more intelligent and practical and is achieved by using artificial neurons and scientific theorems. Compared to natural or human intelligence, AI can be considered superior with regards to its characteristics concerning consistency, ease of duplication and documentation, reliability, and speed (Pannu, 2015).

According to Hussain (2018), AI can be further broken down into three distinct concepts, which highlight different levels of "intelligence":

- *Artificial narrow intelligence* – It consists of the essence or part of a task. Examples would be chat bots or individual response providers like Alexa by Amazon or Siri by Apple.
- *Artificial general intelligence* – It consists of human-level tasks without human interaction, such as autonomous driving, and includes an infinite learning process of the machine.
- *Artificial super intelligence* – It is a vague concept which describes a level of intelligence that surpasses the present capabilities of humankind as we are aware of it today.

Another distinction between "weak" and "strong" AI can be made based on Searle's contribution to the topic as outlined by Flowers (2019) and Martinez (2019):

- *Weak AI* – Based on the concept of weak AI, a computer can be considered a tool that allows one to formulate and validate hypotheses in a more rigorous manner. It is a tool that needs be told what to do and then it will do exactly what it was asked to do and thus, only simulates functions.
- *Strong AI* – In contrast to weak AI, the concept of strong AI thinks of a computer not as a tool that needs to be told what to do but as a computer that has a mind of its own. These machines can process and act independently, eventually fully imitating human intelligence.

4.1.2. Areas and Applications

Nowadays, AI technologies have reached the point where they provide practical advantages in numerous applications. According to Hussain (2018) and Pannu (2015), the most prominent areas of AI include:

- *Language processing* – The skill to comprehend and respond to natural language. This includes the translation from spoken to written language and between different natural languages. Examples include speech understanding, question answering, or information retrieval.
- *Learning and adaptive systems* – The skill to adjust behaviour based on prior experience with the goal of establishing rules concerning the environment based on such experience. Examples include cybernetics or concept formation.
- *Problem solving* – The skill to formulate a problem, plan its solution, and understand when new information is required as well as know the ways to acquire the new input. Examples include heuristic search, interactive problem solving, or automatic program writing.
- *Visual cognition* – The skill to analyse a sensed scene by connecting it to an internal model constituting the perceiving machine's "information about the world" resulting in a framework of relationships among the scenes. Examples include pattern recognition.
- *Modelling* – The skill to establish an internal set of transformation rules that can be applied to predict the actions and dynamics between real life objects. An example of

this would be the modelling of natural systems, such as sociological or biological systems.

- *Robotics* – This area merely combines all above mentioned skills and adds the ability to physically move and manipulate objects. Examples of this area can be found in, for instance, industrial automation (i.e. automated assembly lines).
- *Games* – The skill to receive a set of rules and to translate these rules into a model or framework that enables problem-solving and learning loops to achieve a high level of performance. An example of this area of AI would be chess where a person plays against a chess computer.

The applications of these different areas of AI are manifold. To mention a few, AI is, in addition to agriculture, currently used in the financial world, heavy machinery industry, healthcare sector, and transportation industry (Hussain, 2018; Pannu, 2015).

4.1.3. Machine Learning

Being considered a subset of AI, machine learning (ML) gives computers the ability to learn without being explicitly programmed according to the definition of ML coined by Arthur Samuel in 1959 (Helm et al., 2020; Ongsulee, 2017). Essentially, ML is the study of algorithms that can learn from "experience", which comes in the form of training data, and make data-driven predictions (Liakos et al., 2018). In areas, where building an explicit and well performing algorithm is too complicated or infeasible, ML algorithms, which build a model from sample inputs, are used. These models allow one to generate reliable and consistent results and decisions as well as to uncover hidden insights (Ongsulee, 2017).

Within the field of ML several methods of "learning" exist. Supervised and unsupervised learning account for up to 90 percent of all ML. In addition, the significantly less often used semi-supervised and reinforcement learning exist too (Ongsulee, 2017). Below the four different types of "learning" are outlined according to Ongsulee's (2017) description:

- *Supervised learning* – The algorithm is trained only with labelled input data. That means the algorithm receives the corresponding output to every input example. Therefore, the algorithm can learn by comparing its actual output with the correct output and adjust its model accordingly. This method is often used when historical data can predict future events, such as predicting the likelihood of insurance claims by customers.

- *Unsupervised learning* – In contrast to supervised learning, when using the unsupervised method, the algorithm is trained with unlabelled data. Therefore, the algorithm must comprehend what kind of data is presented with the goal of finding structure or patterns within it. This method can be used to group customers based on common attributes with the goal of improving the effectiveness of marketing campaigns through improved targeting.
- *Semi*-supervised *learning* – This method is used for the same cases one would use supervised learning. However, the algorithm is trained with labelled and unlabelled data which is usually more affordable as unlabelled data is considerably cheaper and more convenient to acquire. An example of this method's application is facial recognition.
- *Reinforcement learning* – By using this method the algorithm learns through trial and error which actions to pursue to end up with the greatest reward. This approach consists of an agent (the "learner"), the environment (everything the agent interacts with), and actions (what the agent can do). The agent receives the greatest reward by taking the right actions within a given period and it can speed up the process by following a good policy. Essentially, the objective of reinforcement learning is finding the best policy. This method is commonly applied in the field of gaming or robotics.

4.2. AI based Technologies in Agriculture

Having outlined the agriculture landscape in SSA with all its challenges and opportunities as well as the fundamental concepts and applications of AI and its sub-category machine learning, it is now critical to view AI in the context of agriculture. This will eventually allow one to combine SSA's agriculture landscape with the state-of-the-art AI based agriculture technologies and infer its potential impact.

To obtain a complete picture of AI based agriculture technologies a systematic literature review is conducted. Furthermore, this strategy sheds light on possibly existing research gaps and consequently, highlights the potential for future research (Moher et al., 2009). The "preferred reporting items for systematic reviews and meta-analysis" (PRISMA) method is, according to Moher et al. (2009), comprised of the following steps: resource identification, selection screening, data extraction, and information synthesis.

4.2.1. Resource Identification

Before starting to identify the relevant resources, several inclusion criteria need to be defined in order to ensure a targeted search. Firstly, the timeframe chosen for this systematic literature review is set to only include articles published within the last four years (2019 to 2022). This will allow the research to focus on state-of-the-art technological developments in the field of AI in agriculture and thus, guarantees practical relevancy by automatically excluding outdated papers and studies.

Secondly, scientific work is detected, such as journal articles, where the following rule is applicable to its titles, abstracts, or search strings:

- ("Artificial Intelligence") AND ("Pest Management" OR "Weed Management" OR "Disease Management" OR "Irrigation Management" OR "Soil Management" OR "Yield Prediction" OR "Crop Management") AND ("Agriculture")

This search string is based on the previously conducted literature review. The databases consulted for the systematic literature review include for instance Emerald Insight, ScienceDirect, SpringerLink, ResearchGate, and Taylor & Francis.

4.2.2. Selection Screening

The main objective was to include articles that clearly describe and assess the real-life impact and implementation procedures of AI based technologies in the field of agriculture. No specific geographic focus was required to meet the inclusion criteria. With respect to the exclusion criteria, all articles that were not published in English, did not have an abstract or granted access to the full document were not considered. Furthermore, articles that did not meet the inclusion criteria, selected timeframe or study objectives of this paper were not considered.

4.2.3. Data Extraction

The first step of the data extraction process included the deletion of duplicates. This step is followed by checking the basic inclusion and exclusion criteria. Next the abstracts were read to ensure that the paper is relevant with regards to the previously defined study objectives. Lastly, the main bodies of the considered papers were analysed to finalize the selection of considered documents for the purpose of the study.

As can be seen in the figure below, 667 articles stored in the Emerald Insight, ScienceDirect, SpringerLink, ResearchGate, and Taylor & Francis databases were identified with the previously defined search string for the purpose of the systematic literature review. Since the same article can appear in multiple databases a check for duplicates was necessary which resulted in the exclusion of 40 duplicate records. Next the remaining records were screened for meeting the basic inclusion as well as exclusion criteria. On this basis 542 articles were removed. The second last step consisted of assessing the abstracts for eligibility which yielded 35 records that were fit for the main text assessment, which was also the last step of this adjusted PRISMA process. Ultimately, 22 articles meeting all requirements were included in the final selection for the study.

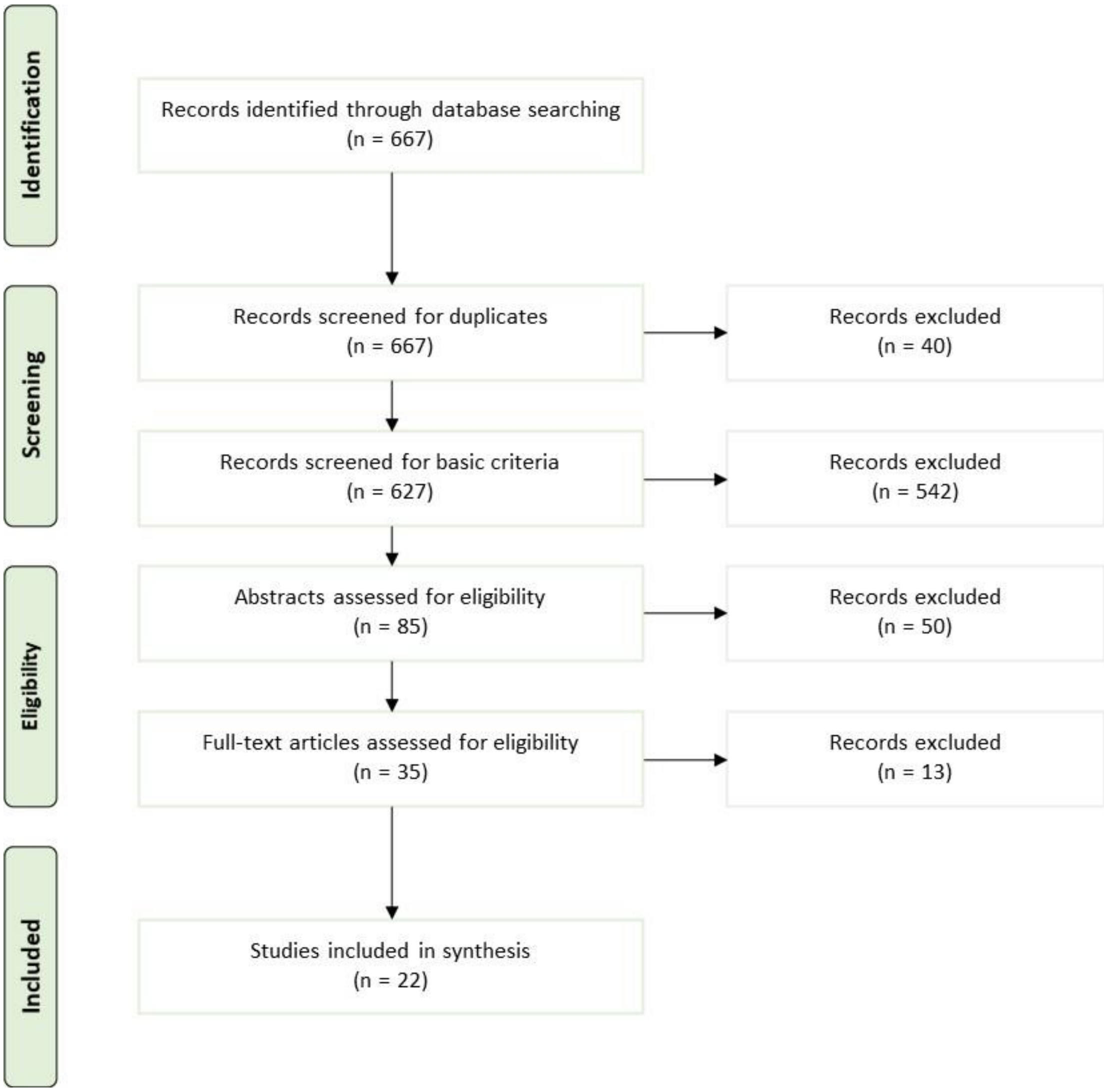


Figure 3 – PRISMA Flow chart by Moher et al. (2009) adjusted

4.2.4. Information Synthesis

The selected 22 articles used for the review consist exclusively of scientific journal articles as can be seen in the table below. This information synthesis section compares, discusses, and combines all relevant insights taken from the selected articles. The aim of this section is to synthesise the application areas of AI in agriculture and distil the technologies that work in tandem with AI.

Authors	Year	Title	Type
Abioye et al.	2020	A review on monitoring and advanced control strategies for precision irrigation	Journal article
Akhter & Sofi	2021	Precision agriculture using IoT data analytics and machine learning	Journal article
Bacco et al.	2019	The Digitisation of agriculture: A survey of research activities on smart farming	Journal article
Bischoff et al.	2021	Technological support for detection and prediction of plant diseases: A systematic mapping study	Journal article
Cao et al.	2021	Wheat yield predictions at a county and field scale with deep learning, machine learning, and google earth engine	Journal article
Charania & Li	2020	Smart farming: Agriculture's shift from a labor intensive to technology native industry	Journal article
Esposito et al.	2021	Drone and sensor technology for sustainable weed management: a review	Journal article
Eugenio et al.	2020	Estimation of soybean yield from machine learning techniques and multispectral RPAS imagery	Journal article
Grieve et al.	2021	The challenges posed by global broadacre crops in delivering smart agri-robotic solutions: A fundamental rethink is required	Journal article
Jha et al.	2019	A comprehensive review on automation in agriculture using artificial intelligence	Journal article
Jiménez et al.	2022	Intelligent IoT-multiagent precision irrigation approach for improving water use efficiency in irrigation systems at farm and district scales	Journal article
Jung et al.	2021	The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems	Journal article
Khattab et al.	2019	An IoT-based cognitive monitoring system for early plant disease forecast	Journal article
Lachman & López	2019	Innovation obstacles in an emerging high tech sector: The case of precision agriculture in Argentina	Journal article
Li et al.	2021	Classification and detection of insects from field images using deep learning for smart pest management: A systematic review	Journal article
Marinoudi et al.	2019	Robotics and labour in agriculture. A context consideration	Journal article
Partel et al.	2019	Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence	Journal article
Preti et al.	2021	Insect pest monitoring with camera-equipped traps: strengths and limitations	Journal article
Putra et al.	2019	Using information from images for plantation monitoring: A review of solutions for smallholders	Journal article
Sagan et al.	2021	Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning	Journal article

Sparrow & Howard	2021	Robots in agriculture: prospects, impacts, ethics, and policy	Journal article
Yuan et al.	2021	Advanced agricultural disease image recognition technologies: A review	Journal article

Table 1 – PRISMA Information Synthesis Articles

With the effects of climate change and related societal challenges, the development of the agricultural sector has recently gained significant traction according to Charania and Li (2020). These authors claim that an agricultural evolution introducing a high level of automation and data-based decision-making to the industry is around the corner. Similarly, Jha et al. (2019) consider the implementation of technologies, such as AI, in agriculture as key to the successful development of the industry to serve the needs of today's world. Enabled through the Internet of Things (IoT) as well as advancements in the area of robotics, AI in agriculture can in fact be leveraged to detect and treat pests, diseases or weeds, optimize soil and irrigation management, or forecast crop yields (Akhter & Sofi, 2021; Charania & Li, 2020).

To ensure that optimal environmental conditions for crop growth are met and potential diseases can be recognised at an early-stage agricultural monitoring systems have been developed by researchers, such as Khattab et al. (2019). Their system consists of three layers with the first on being the hardware module. This module, which can be compared to a weather station, encompasses six different environmental sensors for air temperature, soil temperature/moisture, rain meter, wind speed/direction, leaf wetness, and solar radiation allowing it to measure all related physical quantities. Additionally, the station is solar, and battery powered. A microcontroller sends the data collected by the environmental sensors to the middle layer, which is a cellular transceiver, which in turn sends them wirelessly (for instance via cellular services) as a single SMS to the back-end layer. The back-end module consists of an expert system, an AI software system, that provides recommendations and warnings regarding potential disease outbreaks and can be accessed with any internet-enabled device through a graphical user web interface. In contrast to the disease detection model developed by Khattab et al. (2019), Bischoff et al. (2021), Putra et al. (2019) as well as Yuan et al. (2021) suggest image recognition as a viable option for disease detection. Essentially, all systems are aimed at reducing the overall loss of crop yields due to diseases as well as the usage of chemicals to deal with diseases by providing farmers with real-time information and AI enabled recommendations concerning the status of their crops.

Like diseases, pests pose a major problem for crop production. To have full control over pest outbreaks one needs to have the ability to readily detect and assess pests. While this used to be done manually by pest experts, automation of pest monitoring processes has made significant progress (Li et al., 2021; Preti et al., 2021). In the model suggested by Li et al. (2021) image data is collected with the use of traps or a mobile phone. Insects can be captured with the use of sex-pheromone, sticky-paper, and light traps which automatically take pictures of the caught insects and send them to a remote server. One can also make use of a cellphone to take pictures of insects and upload the collected data, which is a simple solution but comes with the disadvantage of requiring a person to physically visit the field. Next the images are processed by applying machine learning algorithms and the pest density of the field is estimated which serves as the key decision factor for pesticide spraying. One of the biggest challenges for models like these is according to Preti et al. (2021), the necessary power supply which is high since the process of image uploading demands substantial energy.

In line with disease and pest monitoring systems, AI can also be used for weed management (Esposito et al., 2021; Partel et al., 2019). To target the usage of agrochemicals to areas infested with weeds opposed to uniformly spraying a whole field, Partel et al. (2019) developed a smart sprayer. In essence the sprayer includes cameras to gather real-time image data, nozzles used to spray, a smart controller, and a computational unit. Once the sprayer is attached to an all-terrain vehicle driving over a field, the images taken by the cameras are processed in real-time with the use of machine learning algorithms to detect weeds and instantaneously apply herbicide through the nozzles to the targeted area. In contrast to Partel et al. (2019), Esposito et al. (2021) propose the use of unmanned aerial vehicles (UAV), otherwise known as drones, combined with autonomous weeding robots. The drones are equipped with image sensors and can, compared to the smart sprayer system by Partel et al. (2019), cover a much wider area in less time. Furthermore, image sensor equipped drones provide more reliable data compared to satellite-based systems which tend to malfunction in weather conditions such as fog (Esposito et al., 2021).

Another major concern that could be resolved by leveraging the power of AI is the area of irrigation management (Abioye et al., 2020). Jiménez et al. (2022) developed a multiagent irrigation model which consists of intelligent agents being installed on a field and reporting water as well as crop conditions to a master agent which in turn creates an irrigation schedule considering water supply restrictions. In practice, the intelligent agents are comprised of sensor and irrigation stations. While the sensor stations, like the sensors described previously, collect data such as the level of moisture, the irrigation stations are responsible for watering the field. All these stations are wirelessly connected to one central station, which is the master agent. This station autonomously commands which areas of the field to irrigate based on the input data it receives from the sensor stations and defined water supply constraints. As Jiménez et al. (2022) claim their system results in water efficiency gains and automatised irrigation management.

While AI in the field of, among others, disease, soil, or irrigation management largely be considered an enabler to support or substitute human decision making, as discussed in the previous paragraphs, it can also replace manual labor in the area of robotics. According to Marinoudi et al. (2019) AI enabled robots can be used for non-standardized task that include fruit picking or selective weeding. In addition, the list of application areas proposed by Sparrow and Howard (2021) consist of autonomous tractors and harvesters, drones for remote inspection of infrastructure such as irrigation systems, and pesticide spraying. The main goal of applying robotics in the field of agriculture is its potential to increase labor productivity and limit the need for human activity on the field to a minimum (Grieve et al., 2019).

To cope with global agriculture related challenges such as climate change, population growth, and food demand, it is critical to reliably predict crop yields to ensure food security as well as fair trade and policymaking (Cao, et al., 2021). The AI based model developed by Eugenio et al. (2020) uses images taken with remotely piloted aircraft systems that provide information about the phenological stages to predict crop yields. Cao et al. (2021) leverage publicly available data from the Google Earth Engine regarding climate, satellite imagery, and soil conditions to forecast crop yields. In contrast to Cao et al. (2021), Sagan et al. (2021) propose to leverage solely raw satellite imagery data. More specifically, Sagan et al. (2021) use high-resolution data from the WordView-3 and PlanetScope satellite sensors to predict crop yields. The results of their study show that it is also possible to achieve accurate yield forecasts using only satellite imagery.

The specific adoption requirements of all the above-mentioned AI based methods and models differ. However, it can be concluded that leveraging AI in the field of agriculture is possible but requires the combination of multiple technologies (Charania & Li, 2020). Specifically, for most applications microsensors for data collection, networks for data transmission, cloud computing for data processing, and robotics for action are needed. These technologies are not only costly to implement but also require skilled personnel to install, maintain, and use them (Bacco et al., 2019; Charania & Li, 2020). To at least reduce the maintenance efforts, the usage of unmanned aerial systems and satellite imagery instead of fixed sensor networks to collect agricultural data is currently one of the key research areas (Jung et al., 2021; Putra et al., 2019). However, further innovation in the field of agriculture is required but limited by available funding, dissemination of knowledge, market dynamics, institutional support, and available infrastructure (Lachman & López, 2019).

5. Framework Proposal

In this chapter a model consisting of two interconnected parts is presented. The first part highlights the role of AI in SSA's agriculture by relating technologies applied in combination with AI to the most pressing challenges facing agriculture in SSA. These technologies have been inferred from the systematic literature review during which the application areas of AI in agriculture where discussed and underlying technologies were revealed.

The second one consists of a high-level adoption guide showcasing which key requirements need to be tackled to facilitate the implementation of AI based technologies in the studied region. The role and adoption requirements are then validated through expert interviews. Lastly, the results of these interviews are discussed, and the model is adjusted accordingly.

5.1. Assumptions

Based on the knowledge gained through the conduction of a comprehensive (systematic) literature review about the environment as well as state of the art technologies within the field of agriculture the following assumptions are made:

A1: The most pressing agriculture related challenges can be linked to a change in natural or societal factors

A2: The presented AI based technologies can be leveraged to show the biggest potential impact

A3: Mapping use cases of AI based technologies with agriculture related challenges will be critical to propel their adoption

A4: The researched and selected AI based agriculture technologies represent the latest development in the field

A5: The adoption of AI based technologies in SSA's agriculture is largely dependent on high level factors and differs depending on the development stage a region is in

A6: The impact of leveraged AI based technologies in SSA's agriculture goes far beyond the field of its application

A7: A framework showcasing the role and adoption requirements of AI will lead to a leapfrog effect in SSA's agriculture industry

5.2. Reference Model

The artifact developed in this paper consists of two parts as explained before. The first framework aims at mapping the identified key agriculture related challenges in SSA with state-of-the-art AI based technologies. This model will help to understand the true value of AI based technologies and which critical role they can play in further developing the agriculture industry by building more resilience towards external factors. Moreover, the impact of AI, in general, towards societal issues is stressed as well. More specifically the first framework has the following main objectives:

- Mapping and illustrating the prevailing agriculture related challenges with the latest AI based technological advancements
- Supporting relevant stakeholders in the decision-making process of investing into the right technology
- Solving pressing regional nature and society related challenges by providing applicable state of the art solutions
- Helping stakeholders to understand the true value and role of new technologies in a rather traditional industry
- Emphasizing the need to transfer and disseminate knowledge from the developed to developing countries regarding the same industry

		Nature				Society			
		Diseases & pests	Decreasing precipitation	Extreme weather	Limited farmland	Basic infrastructure	Financial support	Food demand	Local expert knowledge
Short-term technologies	Satellite imagery (SI)	SI.1		SI.2	SI.3	SI.4	SI.5	SI.6	SI.7
	Mobile devices (MD)	MD.1			MD.2		MD.3	MD.4	MD.5
Long-term technologies	In-situ sensing (ISS)	ISS.1	ISS.2	ISS.3	ISS.4			ISS.5	
	Unmanned aerial vehicles (UAV)	UAV.1		UAV.2	UAV.3	UAV.4		UAV.	
	Robotics (R)	R.1	R.2		R.3			R.4	

Table 2 – Reference Model Part 1

Considering the state of development and available resources to implement or leverage certain technologies differs per country in SSA, it was decided to split the respective technologies as discussed in the model in short and long-term technologies. Short-term technologies are assumed to be less resource intensive and thus, relatively soon to be available for all countries within SSA. In contrast, long-term technologies are characterised by high resource requirements and therefore, will only become available in the long run in SSA except for relatively well developed and financially stronger countries such as South Africa (Routray et al., 2019; Say et al., 2018).

5.2.1. Short-term Technologies

Satellite Imagery

SI.1: Rising temperatures are expected to promote the likelihood of spreading diseases or pests which is detrimental for the agriculture industry (Pereira et al., 2017). Satellite imagery can be used to detect and even predict areas affected by these which allows farmers to take immediate action and in the best case even prevent the development of diseases or pests (Bischoff et al., 2021).

SI.2: Due to an increasing number of extreme weather events in SSA, the risk of food shortages increases (Cao et al., 2021; Woetzel et al., 2020). Therefore, a necessity to accurately predict crop yields to take immediate action in case of a potential food shortage exists. Sagan et al. (2021) as well as Cao et al. (2021) outlined in their studies that satellite imagery as input for machine learning algorithms can be successfully applied to accurately predict crop yields.

SI.3: With its ability to be used to detect, among others, diseases or weeds at an early stage, satellite imagery can have a significant positive impact on land productivity (Bischoff et al., 2021; Esposito et al., 2021). This in turn helps to deal with the prevailing challenge of limited arable land in SSA and the need to increase land productivity (Kassie et al., 2011; Mellor, 2014).

SI.4: Since satellite imagery is a remote sensing technique, it is possible to gain all information on a region without being physically present. Additionally, no infrastructure in the target area is required considering the remote nature of technology (Jung et al., 2021). Therefore, the barrier of lacking infrastructure in large parts of SSA can be overcame with satellite imagery (Lachman & López, 2019).

SI.5: Considering satellite imagery is a scalable form of remote sensing where freely available data to train AI algorithms to, among others, detect diseases or predict crop yields, stems from existing satellites, the financial investments to access these can be considered relatively low compared to other discussed technologies (Jung et al., 2021).

SI.6: With the previously discussed impact satellite imagery has in the agriculture industry due to its application in disease, pest, and crop management, it significantly enhances food production (Bischoff et al., 2021; Esposito et al., 2021; Sagan et al., 2021). This is necessary to deal with the ever-increasing food demand in SSA (Van Ittersum et al., 2016).

SI.7: As discussed above, satellite imagery is applied remotely and hence, professionals gathering and processing the data to detect diseases or predict crop yields do not need to be on-site

(Jung et al., 2021). This allows for selecting from a global pool of experts and does not necessarily require the dissemination of knowledge in SSA, which is currently a roadblock for the development of its agricultural landscape (Lachman & López, 2019; Salami et al., 2010; Sims et al., 2016).

Mobile devices

MD.1: With rising temperatures and an increase in climate variability the potential for diseases and pests is expected to increase (Pereira et al., 2017). Mobile devices can be used for disease and pest monitoring and help to identify them at an early stage improving a farmer's plant treatment strategy and ultimately restricting the expansion of diseases and pests (Preti et al., 2021; Putra et al., 2019).

MD.2: Mobile devices can be used to gather field data regarding the state of plant health to detect pests and diseases (Li et al., 2021; Preti et al., 2021). Furthermore, they can serve as an interface for an AI driven decision support system (Putra et al., 2019). Therefore, mobile devices can contribute to the necessary increase in land productivity in SSA (Kassie et al., 2011; Mellor, 2014).

MD.3: Since the implementation of a mobile based decision support system in agriculture relies, in addition to a server used for running algorithms, solely on a mobile device, the need for financial resources can be considered relatively low (Putra et al., 2019).

MD.4: By helping farmers with disease and pest management, mobile devices play a role in improving overall crop yield to counter the increase in food demand in SSA (Pereira et al., 2017; Preti et al., 2021; Putra et al., 2019; Van Ittersum et al., 2016).

MD.5: Since the handling of mobile devices can be considered rather simple and the data processing via web services submitted image data can be done remotely, no local expert knowledge is required to leverage this technology as an AI driven decision support system (Putra et al., 2019).

5.2.2. Long-term Technologies

In-situ sensing

ISS.1: In-situ sensors can also be used to detect diseases which are a result of increased climate variability (Pereira et al., 2017). The multi-sensor expert-system model developed by Khattab et al. (2019) can be leveraged for effective disease management.

ISS.2: To deal with a lack of precipitation and the threat of desertification in SSA (Abioye et al., 2020), local sensors can be leveraged for data collection to monitor moisture levels and apply smart irrigation management solutions, which can increase the water efficiency in the agriculture industry (Jiménez et al., 2022; Routray et al., 2019; Sultan & Gaetani, 2016).

ISS.3: Extreme weather events have a negative effect on the predictability of crop yields (Cao et al., 2021; Woetzel et al., 2020). To counter this challenge, in-situ sensors can be used to accurately monitor the nutritional health of crops to enhance yield planning (Khattab et al., 2019).

ISS.4: With relevant use cases in disease, irrigation, and crop management in-situ sensors significantly improve the agricultural productivity needed to deal with SSA's increasingly limited farmland and rising population density (Jiménez et al., 2022; Khattab et al., 2019; Mellor, 2014).

ISS.5: With its significant impact especially on irrigation and disease management, in-situ sensing can be considered a technology that increases food production to deal with the rising food demand in SSA (Khattab et al., 2019; Jiménez et al., 2022; Van Ittersum et al., 2016).

Unmanned aerial vehicles

UAV.1: Similar to mobile devices, UAVs can be used to detect disease or pest impacted areas of farmland at an early stage (Pereira et al., 2017). This is achieved by leveraging image recognition-based algorithms (Putra et al., 2019).

UAV.2: With a higher likelihood of extreme weather events, the risk of food shortages increases as well (Cao et al., 2021; Woetzel et al., 2020). Consequently, it is critical to accurately predict crop yields which can be achieved by using UAVs to gather data on the state of fields as input for machine learning prediction models according to Eugenio et al. (2020).

UAV.3: Considering the impact UAVs can have in the area of disease and pest management as well as yield prediction, it is clear that this technology enhances agricultural productivity which is needed to deal with limited farmland and increasing population density (Eugenio, 2020; Mellor, 2014; Putra et al., 2019).

UAV.4: UAVs do not require basic infrastructure such as access to electricity or internet when being used and they also do not rely on road systems to be transported to the area where they are used. Therefore, they can support SSA's agriculture industry to circumvent the issues regarding the region's undeveloped infrastructure (Jung et al., 2021; Mellor, 2014; Putra et al., 2019).

UAV.5: Given the many uses of UAVs to address agricultural challenges such as disease and pest control and the associated improvement in crop yields, this technology can be seen as having a significant impact on meeting rising food needs in SSA (Eugenio, et al., 2020; Putra et al., 2019; Van Ittersum et al., 2016).

Robotics

R.1: Once diseases and pests have been detected, AI enabled robots in the form of, among others, autonomous tractors can replace manual labor to treat the infested areas. More specifically, according to Sparrow and Howard (2021), robots can be used for pesticide spraying and based on the research done by Marinoudi et al. (2019) for selective weeding.

R.2: Similar to its application in disease and pest management, robotics can play a major role when it comes to enabling irrigation systems. Irrigation robots can help to automate irrigation management and replace significant parts of otherwise manual tasks (Grieve et al., 2019; Jiménez et al., 2022; Sparrow & Howard, 2021).

R.3: Considering AI enabled robots can be used for disease, pest, and irrigation management they contribute positively to farmland productivity and help SSA's agriculture to deal with the challenge of rising population density and farmland scarcity (Grieve et al., 2019; Jiménez et al., 2022; Mellor, 2014; Sparrow & Howard, 2021).

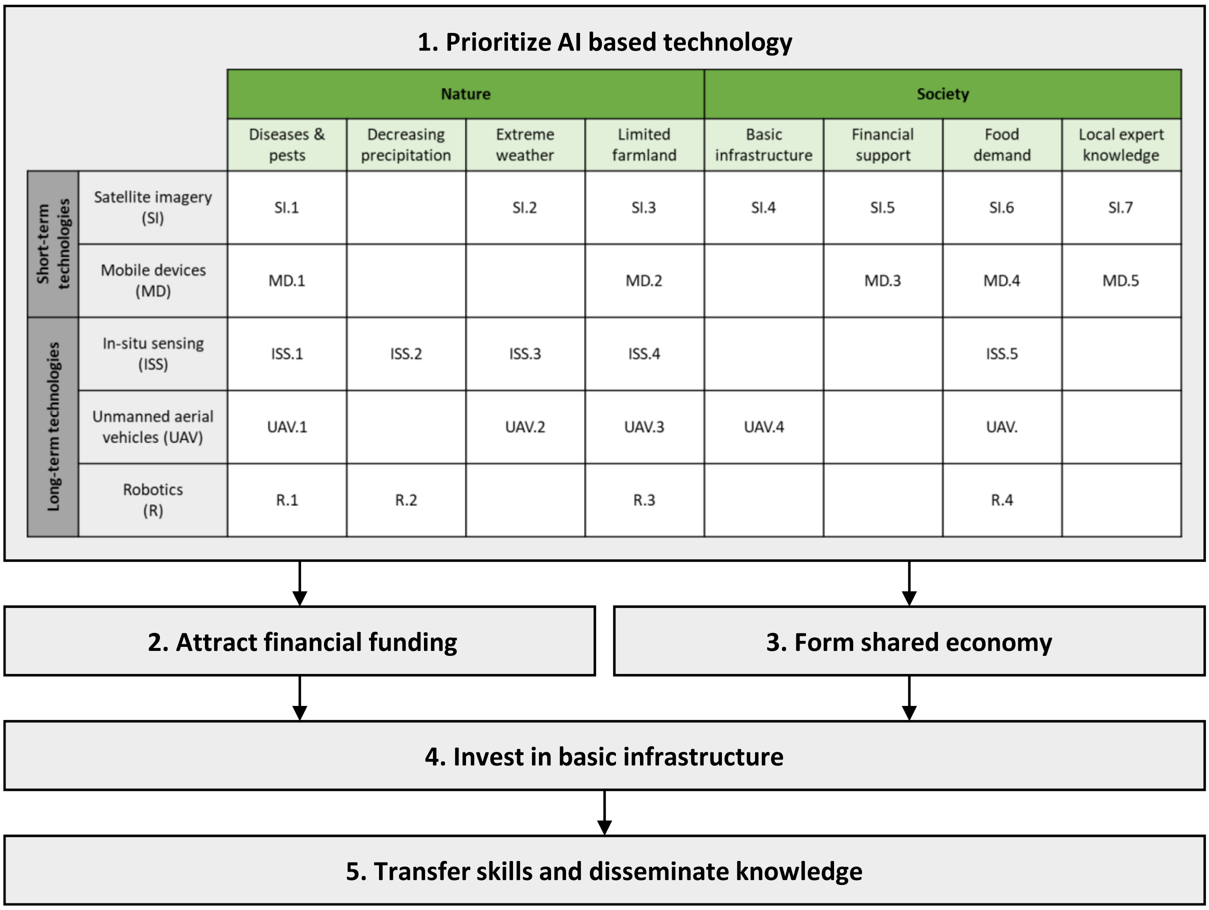
R4.1: By improving farmland productivity through robotics-based solutions in the areas of irrigation management as well as disease and pest treatment, this technology has great potential to help SSA to close the food supply gap (Grieve et al., 2019; Jiménez et al., 2022; Sparrow & Howard, 2021; Van Ittersum et al., 2016).

5.2.3. Technology Adoption

The second part of the model aims at highlighting the basic requirements that likely need to be met to adopt and implement AI based technologies mentioned in the reference model part 1, with a focus on the so-called long-term technologies. The main objectives of this framework include:

- Illustrating the key external factors currently limiting the adoption of new technologies in SSA
- Guiding relevant stakeholders in investing into the right areas to improve the conditions for technology adoption
- Creating a basic understanding that some form of upfront investment is needed to start a developing process

- Emphasizing the distinctiveness but interconnectivity of external factors limiting technology adoption in SSA
- Offering solutions in how to create an environment supporting the implementation of AI based methods in agriculture



		Nature				Society			
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	Robotics (R)	R.1	R.2		R.3			R.4	

Figure 4 – Reference Model Part 2

1. Prioritize AI based technology

Taking the reference model part 1 as an input, it is the first step to accurately prioritize the respective AI based technologies. To achieve this prioritisation, impact and urgency should be considered. These dimensions have been successfully used in prioritizing strategic issues and can be universally applied (Ansoff, 1980).

Firstly, the impact, which is strongly dependent on the context of the application, should be assessed. To accomplish this, the most pressing environmental challenges in the region of interest need to be determined. This allows one to understand in which area a technological solution needs to be found. For instance, if desertification due to a lack of precipitation is the main factor restraining agricultural production, the implementation of irrigation management solutions should be given priority over the adoption of disease monitoring systems.

Secondly, a specific technology needs to be chosen based on the urgency of its implementation. Consider a scenario where time is critical. Under these circumstances, it is not feasible to opt for a technology that would require the construction of certain infrastructures that are currently lacking, such as a power grid. In this case, depending on the environmental challenge, the adoption of satellite imagery could be a favoured solution.

2. Attract financial funding

To implement long-term technologies significant funding is required. However, financial support remains one of the biggest barriers to develop SSA's agriculture industry (Dupoux & Zrikem, 2017). This could potentially be overcome as investments in agriculture in general are considered an emerging and increasingly competitive asset class (Ducastel & Anseeuw, 2017).

One key area to focus on to attract more financial investments is impact transparency. Ducastel and Anseeuw (2017) as well as Miller and Ono (2016) stress the fact that data regarding investment deals in SSA's agriculture industry is limited but knowing risk-return patterns is critical to attract funding bodies. Consequently, impact reporting processes should be proactively set up to keep track of the technology impact and communicate the results to investors.

On a more institutional level, it is necessary to revamp the current policy and regulatory system in SSA to provide investors with the enabling environment needed to ensure a smooth investment process. Coordinated public-private partnerships, as well as clear policies regarding compliance with contractual obligations and capital repatriation, are tools that can help create the appropriate investment conditions (Miller & Ono, 2016).

3. Form shared economy

Considering the implementation of new technologies is rather costly and the agricultural landscape in SSA is dominated by smallholder farmers bridging this dilemma could be achieved by applying a shared economy approach (Bacco et al., 2019; Gollin, 2014). This would result in multiple smallholders together with large-scale farmers to form communities, collaborate, and utilize the implemented technology on a larger more affordable scale.

The main goal of a sharing economy approach is to ensure a high degree of utilization for otherwise underutilized goods (Böcker & Meelen, 2017). While this concept was initially applied by companies such as Airbnb where otherwise empty apartments are "shared" it could be adapted and transferred to other cases (Constantinou et al., 2017). Looking at the agriculture industry in SSA, for instance, multiple smallholder farmers may purchase and use a technology, such as UAVs, together as a structured union.

To ensure accessibility and efficiently make use of the technology, two points should be considered. Firstly, the formation of a shared economy might lead to an increase in the technology purchasing price as vendors might sell their product at a higher price to a farmer union versus an individual farmer. This would counter the purpose of a shared economy making a technology more affordable and thus, accessible to farmers with limited financial resources, by sharing it. Therefore, a vendor due diligence should always be conducted with regards to the asking price of the to be acquired technological product to ensure full market transparency. Secondly, a scheduling tool will be required. This will allow all involved parties to fully utilize the technology and collaborate in an organized manner (Böcker & Meelen, 2017; Constantinou et al., 2017).

4. Invest in basic infrastructure

Depending on the selected technological solution, it might be necessary to invest into basic infrastructure. While the application of drones is independent of basic infrastructure, basic cellular networks might be required for sensors to communicate and share data (Jung et al., 2021; Preti et al., 2021; Putra et al., 2019). Even more critical for most AI based applications is a functioning local power grid, which is currently lacking in SSA (Mellor, 2014).

One solution to implement communication networks could lie in the application of micro satellites operating from space. This technology would effectively make land-based networks obsolete and could provide the most rural areas of SSA with internet access without the need for installing cable systems (Lavery et al., 2018).

To bridge the electricity demand and supply gap in SSA, a shift from fossil to renewable energy should be considered. Africa's potential for renewable energy is tremendous including geothermal, wind, hydro and solar power. Not only are these energy sources renewable and CO_2 neutral but a combination of them can be used in all regions of SSA providing a high degree of flexibility compared to energy sources such as coal or gas (Chakamera & Alagidede, 2018).

Africa is one of the least integrated regions in the world. However, to achieve a sufficient level of basic infrastructure such as communication networks and access to electricity the regions and respective leaders and stakeholders within SSA must work in tandem as the implementation success rate of large-scale infrastructure projects is highly reliant on the degree of intraregional collaboration (African Union, 2015).

5. Transfer skills and disseminate knowledge

Lastly, it will be critical to disseminate the required knowledge and transfer the relevant skills to all stakeholders involved in applying the AI based solutions daily (Lachman & López, 2019). This is still a major problem in SSA as institutional support is significantly limited (Salami et al., 2010; Sims et al., 2016).

A set of initiatives could prove to solve the issue of knowledge transfer. Firstly, close collaboration of local and foreign businesses based on co-operative arrangements backed by governments can help to disseminate knowledge provided the right balance of local and foreign business exists. This also implies the importance to establish effective industry institutions and policies to attract foreign direct investments such as tax benefits (Osabutey & Jackson, 2019; Osabutey & Jin, 2016).

Another solution could lie in the formation of independent business circles comprised of smallholders as well as large scale farmers to engage in a frequent discussion and exchange information about the technologies to foster adoption. All potential solutions to disseminate technology knowledge in SSA are further enhanced by an effective local education system (Osabutey & Jin, 2016).

5.3. Model Validation

To validate the beforehand outlined model, expert interviews were conducted. The reason for choosing to use expert interviews and thus, a qualitative and potentially harder to control validation method, lies in the fact that the field of study is highly topical. Therefore, relevant as well as accessible datapoints that would allow one to opt for a more quantitative validation approach are currently still lacking.

The expert interviews were conducted with the use of a previously developed interview guideline. This question guideline allows the interviewer to consistently follow a structure during the interview process, which in turn reduces the interviewer's inherent bias and ensures a maximum level of comparability of the interview results. The interview questions itself were designed in a way to strike the right balance of topic relevance and expert insights. More specifically, the goal was to allow each interviewee to share his whole expertise and knowledge considering his individual background within the scope of the study to potentially generate novel insights while accounting for comparability of all interview results. With the reference model having a holistic approach on the topic of AI in SSA's agriculture, each expert was able to equally contribute to the validation process despite their slightly differing focus of work or research. The table below outlines each expert's professional background, area of expertise, regional focus, and domain.

ID	Profession	Expertise	Region	Domain
E1	Agricultural Consultant and Project Officer @ Caritas	African Agriculture	Burundi South Sudan	Industry
E2	Co-Founder @ Prime Agro Seeds Board Strategy Advisor @ Rural Farmers Hub	African Agriculture Agricultural Technology Artificial Intelligence	Nigeria	Industry
E3	Senior Researcher @ Graz University of Technology CTO @ SelectionArts Intelligent Decision Technologies	Artificial Intelligence	Austria	Academic
E4	Head of Agronomic Innovation @ MAR.FRU SAS Agrotechnical Consultant @ Agriculture Worldwide Services Postgraduate Researcher @ Independent	African Agriculture Agricultural Technology	Senegal	Academic Industry
E5	CEO & Co-Founder @ AgriEye	African Agriculture Agricultural Technology Artificial Intelligence	Sub-Saharan Africa	Industry

Table 3 – Expert Interviewees

The interviews were conducted individually during the month of June 2022. All interviewees agreed to recording the interview for transcription purposes, but the video material may not be made public. The transcripts can be found in the appendix section.

5.4. Discussion

In general, all the interviewed experts consider the framework to be exhaustive. There is a consensus that the most important agricultural challenges, AI based technologies as well as adoption requirements are included and mapped accurately. Furthermore, by specifically pointing out the grouping of technologies based on their adoption effort, expert 1 and expert 2 underpinned the decision to categorize the technologies in the model in short and long-term.

When considering the usefulness of the model all interviewed experts concluded that the model is in fact useful for multiple stakeholders. Expert 1 and expert 2 highlighted that the impact of the developed theoretical model lies in its capability to raise awareness for new solutions and thus, triggers change. More specifically, expert 1 mentioned that especially certain African governments like the one in the Democratic Republic of the Congo are simply unaware of the potential of AI based solutions in agriculture and could greatly benefit from the model with its outlined implementation requirements. Additionally, expert 2 suggested that based on theoretical frameworks partnerships between the private sector, public institutions and research facilities can be formed which are not only needed to implement solutions but also to sustainable preserve and disseminate knowledge.

All experts appreciated that the framework included a basic adoption guideline that needs to be followed to create the conditions that are required to successfully implement some of the AI based technologies. Moreover, expert 1, expert 2, and expert 4 saw the greatest use of the model in its ability to show how a leapfrog effect can be achieved. Among others, the proposed model shows the potential of satellite imagery and mobile devices to circumvent challenges such as a lacking electricity network or missing financial means (E1, E2, E4). Thus, the framework can contribute to the adoption of such short-term technologies on a wider scale.

In addition to the supportive statements made about the framework, each interviewed expert had also constructive feedback regarding ways to further enhance the developed framework. This valuable expert feedback serves as the basis for the later presented revised and improved version of the model.

With regards to the exhaustiveness of the framework, expert 2 suggested that a major agriculture related challenge for farmers is their lacking access to basic inputs such as seeds, fertilizers, and pesticides. While the usage of fertilizers could potentially be circumvented by selecting fertile land based on satellite imagery analysis, the need to access seeds and pesticides cannot be substituted by technology (E2). Expert 2 and expert 4 both claim that access to markets for agriculture inputs but also financial instruments is the predominant challenge and not the attraction of funding. Smallholders need to have access to the bank system to take out cheap loans and to the agriculture market to buy inputs which are currently simply not sufficiently available in SSA (E2, E4).

According to expert 2 one step that is missing in the model is a prototyping or testing phase. Even though the technologies are proven to work, the environment in which they are currently applied in might differ from SSA (E2). Therefore, including a testing phase into the adoption plan of the AI based technologies is suggested.

Expert 5 noticed a missing match between satellite imagery and decreasing precipitation. Satellite imagery can be used to analyse soil conditions up to two meters below the surface, which allows one to receive a clear picture with regards to moisture levels which can in turn support irrigation decisions (E5).

Expert 1 and expert 4 pointed out that the implementation of the model assumes the survival of smallholders by default. However, currently a large share of smallholders is fighting to survive. Thus, expert 1 proposes to include governmental support to cover the basic needs of farmers as a pre-requisite to be included in the model. Similarly, expert 4 claimed that the presented AI based technologies are focused on increasing land productivity opposed to land expansion. However, yields must tenfold to allow farmers a secure income to ensure survival which cannot be achieved by solely improving the output per square meter of farmland through AI based technologies and therefore, land expansion approaches must be considered in a solution to further develop SSA agriculture as well (E4).

The critique of expert 1 also concerned the geographical applicability of the model. While the model was developed with the intention to be applied in all SSA countries, regional differences are enormous and therefore, it is suggested to further distinguish between regions especially with regards to the adoption requirements (E1).

One point of improvement raised by expert 3 and expert 5 included the level of granularity of the model. While they do understand the scope of the research, they would propose to go into more depth. This increased level of depth could be achieved by analysing different underlying algorithms that ultimately make up the decision support system or further break down the individual technology categories. Similarly, expert 2 critiqued the level of detail with regards of the adoption requirements and would suggest developing a clear implementation roadmap for each AI based technology.

Lastly, expert 4 raised a challenging thought that AI can never replace human intelligence but in his opinion, this was the message the developed model was conveying. This expert claimed that a hybrid model where humans leverage AI based technologies but are not entirely replaced by it is the way going forward.

5.5. Revised Model

Based on the collected feedback and criticism pertaining to the scope of this thesis the previously developed model was revised as seen below. More specifically, a match between satellite imagery and decreasing precipitation (A), the establishment of market access (B), and the inclusion of a testing phase (C) were added.

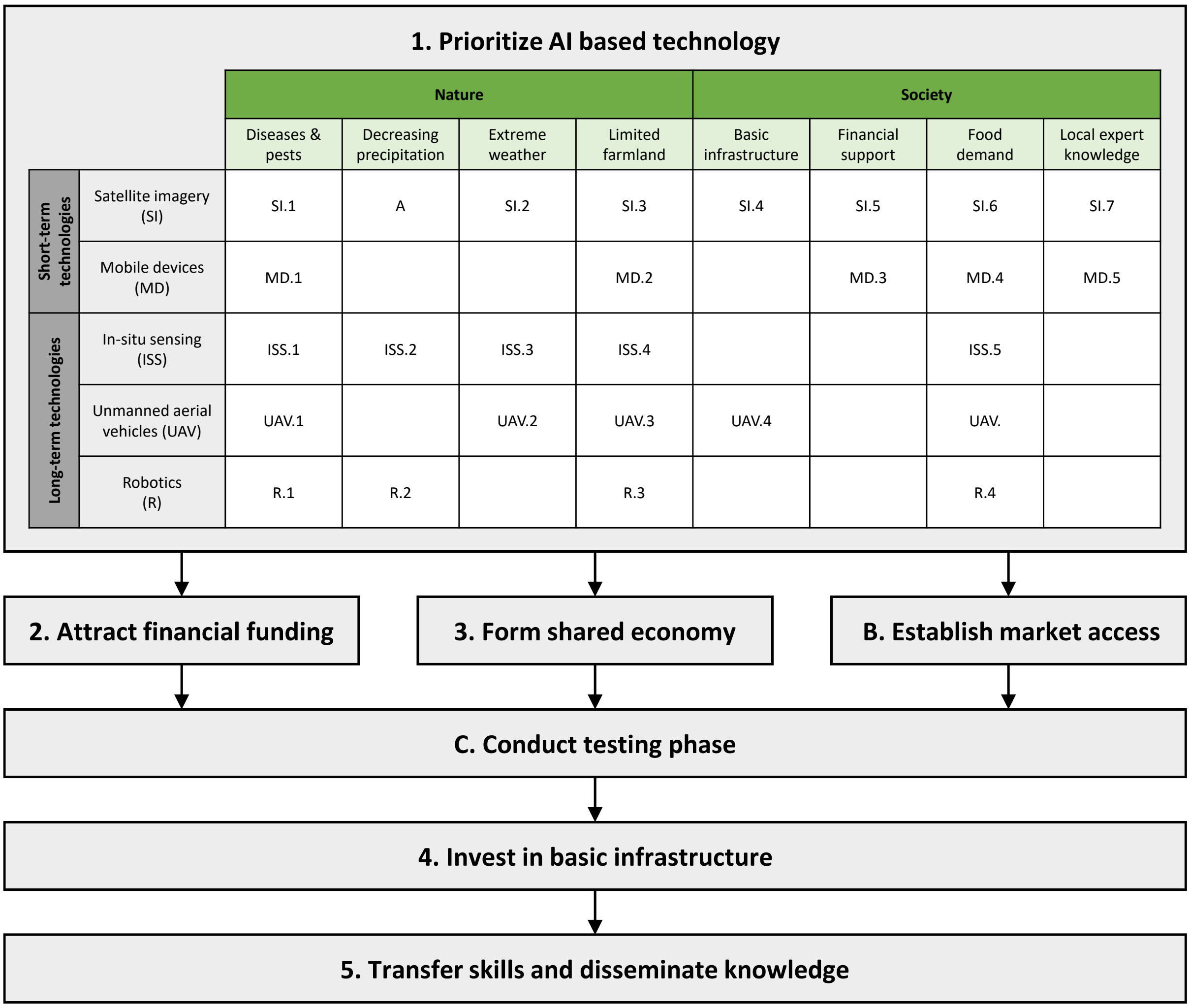

Figure 5 – Revised Model

A) According to expert 5 satellite imagery can be used to analyse soil conditions such as moisture levels below the surface which can in turn support irrigation decisions (E5). Consequently, this technology can be applied to deal with decreasing precipitation and a match was included in the model.

B) The access to markets for agriculture inputs but also financial instruments is according expert 2 and expert 4 an adoption requirement to successfully implement and leverage the presented AI based technologies.

C) Despite the maturity level of the technologies included in the model, a testing phase was added. This should allow stakeholders to validate the expected impact a certain technological solution should have before committing more significant investments into infrastructure, training projects and roll-out processes (E2).

6. Conclusion

The agriculture industry in SSA faces numerous challenges including diseases and pests, decreasing precipitation, extreme weather events, limited farmland, lacking infrastructure, missing financial support, increasing food demand, and limited local expert knowledge. AI based technologies in the field of agriculture that could potentially be used to deal with some of the challenges exist but are currently mostly applied in other regions of the world. Current literature lacks research on how these technologies could solve or circumvent agriculture related challenges in the context of SSA and what general requirements for their successful adoption need to be met. To close this gap, the following research question was established:

Can the adoption of AI based technologies solve sub-Saharan Africa's agricultural challenges?

This question was answered by the development of a model that showed which AI based technologies exist to solve or deal with the most pressing agriculture related challenges in SSA as well as highlighted which critical requirements need to be met to successfully adopt (long-term) technologies in SSA. Based on the systematic literature review it can be concluded that numerous AI based technologies exist which can be leveraged to circumvent most of the pressing challenges SSA's agriculture faces. The basic conditions that need to be created by individual stakeholders to successfully adopt them are clear as well.

The model that combines both insights was validated by experts who consider it an exhaustive and useful framework proving again that AI based technologies can be leveraged to tackle SSA's agricultural challenges. Through a critical feedback process the model was revised and can now contribute as a high-level guideline for the adoption of AI based technologies in SSA.

6.1. Synthesis of the Research

This paper was developed in a structured manner. First, a general literature review was conducted with the goal of outlining the agriculture landscape in SSA with all its related challenges. This step was followed by a systematic literature review of state-of-the-art AI based technologies in agriculture. The third step consisted of defining a nexus regarding how these AI based technologies can be leveraged to deal with the previously researched agriculture related challenges in SSA in the form of a matrix model. Then, adoption requirements for the technological solutions were added to the matrix complementing the model. The final framework was validated through specifically selected experts and a revised version of the artifact was created.

6.2. Research Limitations

One of the limitations of this study was the available literature. Even though many papers in the field of agriculture exist, it proved to be difficult to find recent and relevant papers that included practical examples of how certain technologies are applied in the field. Furthermore, no similar frameworks matching agricultural challenges and technologies in other contexts could be found which confirmed the research gap but hindered the intended research strategy to a certain extent.

Another limitation is the validation process. While expert interviews form a solid foundation for a qualitative validation process, it is to be noted that the framework itself is rather broad and thus, the capability of an expert to speak about the whole model can be questioned. Due to time restrictions, no additional validation round of the revised model was conducted as suggested by the design science research approach which could have partially countered this limitation. Nevertheless, the selected experts appeared to be confident about the topic of discussion.

While the purpose of the study was to analyse and map a multitude of agricultural challenges and AI based technologies and find common adoption requirements the level of detail it was conducted in can be considered a limitation. Similarly, the regional focus on SSA could be criticised if one considers the differences among the included countries as too significant.

6.3. Future Research

Looking at recommendations for future research the first suggestion would be to increase the level of detail by selecting a single AI based technology such as satellite imagery and analyse it in more depth. This could mean as much as evaluating its different underlying algorithms and analysing the technology in the context of one highly homogeneous country or region. This will allow one to also develop a specialised implementation roadmap for the technology with clear action steps and ideally the potential to conduct a quantitative study for impact measurement.

Moreover, it would be interesting to gain a better understanding of the interaction and performance difference between professional agronomists and AI based technologies. In that sense a study could be created that compares the impact of supporting smallholders through training from an educated agronomist versus for instance a decision-making system based on remote controlled satellite imagery or the use of mobile devices.

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Appendix

Interview with Expert 1

Question 1: Do you believe the proposed model to be exhaustive?

From what I can tell all relevant agriculture related challenges that come up in my mind would fit into one of the buckets you propose in your model. I can personally not stress enough the challenge related to basic infrastructure. To be honest it is for us Europeans unbelievable to see how undeveloped most African countries still remain. Not only internet and electricity are missing but also road systems are partly non-existent. You also mention extreme weather events which immediately reminds me of the Victoria Lake. This lake and its connected river systems are currently flooding surrounding land areas whereas other parts of Africa experience extreme heat waves and droughts.

Looking at the technologies you mention I believe the list to be exhaustive and would stress that as of now especially mobile devices with apps for image based plant disease detection could be an interesting technology to be adopted in the rather short-term. I would also consider the more expensive technologies to be long-term since we tend to overestimate the financial resources smallholders have which make up the majority of African farmers.

Question 2: Do you consider the proposed model as useful and why (not)?

I do consider the model to be useful especially when it comes to raising awareness for the need to deal with certain agriculture related challenges and the potential role technology can play. Although I would mention that especially short term technologies such as mobile devices should be the focus. Governments like the one in Congo where limited awareness for agricultural technologies exists would surely benefit from knowing models like this exist. It would help these regions to come up with clearer tactics to develop their agriculture industry.

Furthermore, this model highlights how certain agriculture related challenges can be circumvented. For instance, we see that a reliable internet connection, working grid network and financial support is not the norm in most African countries. However, the model clearly shows that with the use of satellite imagery neither electricity nor internet is needed on field site and rather inexpensive solutions in the form of mobile devices exist. These are great opportunities for the African agriculture.

Question 3: Do you have any criticism against the proposed model?

The only concern I have comes with regards to the context in which you would like the model to be applicable in. While I do consider the model to be useful I know that regional differences are significant between West, Central and East Africa or between anglophone and francophone influenced countries. For example, East African countries like Kenia have a significantly more developed infrastructure system and English as a national language which helps to disseminate knowledge about new technologies. After all, new technological advancements are developed and first presented in an English environment.

These differences play a major role in adopting new technologies and therefore it will be difficult to create a framework that equally applies to all regions in Sub-Saharan Africa. Your model does show that certain technologies are considered long-term and challenges such as a lack of basic infrastructure exists which is true for pretty much all countries in Sub-Saharan Africa but the extent to which it is true differs.

Question 4: Do you have any suggestions on how to further improve the proposed model?

The one thing I would make more obvious in your framework is the requirement that in order to start thinking about tackling the mentioned agriculture related challenges we need to put African farmers in a position where their basic survival needs are met. As of now farmers literally fight for survival and investing in basic infrastructure or creating shared economies for advanced technological tools will be of no use. Therefore I would add governmental support to ensure the needs to survive are met as pre-requisite step to the framework to develop the African agriculture. After all the majority of the African population relies on agriculture to make a living and thus, it is fair to consider the population's survival as an agriculture related challenge as well.

Interview with Expert 2

Question 1: Do you believe the proposed model to be exhaustive?

Looking at the model and the technologies you mention I do not see anything to add on the same level. However, I will mention that basic database management serves as the fundamental technology for all of your mentioned solutions even if database management is not the technology an end-user of a mobile device or drone will have to deal with.

The agriculture related challenges could be extended by mentioning the issue of getting the appropriate agriculture inputs such as seeds, fertilizers and pesticides. Additionally, I would like to mention that many farmers lack not only the means to fund (basic) tools and mechanisation but also access to the markets where tools are available and can be bought which is an agriculture related challenge as well. I do appreciate the fact that you mention local expert knowledge as a challenge because I consider it one of the most critical issues that agriculture as well as technology related knowledge is not disseminated properly in places like Africa where it is usually only passed on from generation to generation within one single family.

Question 2: Do you consider the proposed model as useful and why (not)?

I do consider models like yours as useful. I think in general the private sector and academia should collaborate a lot more to advance each other and both be part of the solution space. This will allow theoretical frameworks like yours to have a higher degree of practicality and in return serve as scientific validation for the impact of practices conducted by the private sector. Furthermore, frameworks like yours contribute not only to knowledge creation but also to knowledge retention which I consider to be critical.

For your model especially I would like to say that it clearly highlights surrounding requirements such as the need to form shared economies for smallholders that need to be taken care of before one can effectively adopt technological solutions. I consider these types of adoption guidelines to be extremely valuable. Furthermore, it shows the leapfrogging potential of solutions like satellite imagery and thus, highlights ways to develop the agriculture industry at a relatively fast pace.

Question 3: Do you have any criticism against the proposed model?

What I would criticise about the model is that it kind of neglects the foundation of all technologies that are mentioned which in my opinion is database management and analytics. Even though I do understand that database management and analytics should be automated and invisible for the end users of the mentioned technologies. If this is not the case however, the adoption of your framework might not generate enough impact compared to the noise it comes with. By that I mean for instance the data captured by drones needs to be analysed and its insights need to be distilled and presented in a user friendly way to generate impact and avoid noise. It is again all related to the issue of local expert knowledge which you have mentioned already in your list of agriculture related challenges in society.

Question 4: Do you have any suggestions on how to further improve the proposed model?

As mentioned before, I would add the challenge of agricultural inputs such as seeds, fertilizers and pesticides which improve resilience to certain weather conditions, diseases and pests as well as the access to markets for agricultural tools to the list of challenges.

Furthermore, I would consider adding an additional basic requirement which would be “awareness”. All stakeholders but especially the farmers themselves need to be aware of the benefits the implementation of technology. If this is not given they will not be committed and adopting technologies will be impossible. What could help with that as well is prototyping. I believe this step should be included in the model as well as testing technologies in a diverse region such as Sub-Saharan Africa is absolutely critical before committing to a solution and starting to attract funding as well as form a shared economy around it.

While this might be too detailed for your current framework I do believe it would be worthwhile to look into developing specific roadmaps with time-based milestones for each technology to be adopted. Only then progress can be tracked and implementation efforts increased to an extent where practical impact is visible.

Interview with Expert 3

Question 1: Do you believe the proposed model to be exhaustive?

Considering my background I am not aware of technologies that have already been developed and are missing in your model. Even though it is on a different level than the technologies you describe I do miss the area of data mining in your model even though one can argue it is included in the foundation of all the mentioned solutions. Due to my background I cannot speak in detail about the agriculture related challenges but they seem exhaustive for me.

Question 2: Do you consider the proposed model as useful and why (not)?

From an academic point of view frameworks that match new technologies with prevailing challenges in any context can be considered useful. Even more value is added when you address the conditions that need to be met in order to adopt these technologies as well. For this reason I would definitely consider your model to have a positive contribution.

Question 3: Do you have any criticism against the proposed model?

It is not necessarily criticism against your particular framework but I would argue one can go into even more depth when looking at the technologies. I have a strong background in artificial intelligence and would argue that the underlying algorithms play a major role in the selection process of the right technology as well. In that sense it might be out of scope for your thesis but could be interesting to dive into for future research.

Question 4: Do you have any suggestions on how to further improve the proposed model?

Similarly what I said before I would argue that the analysis of the underlying algorithms would yield interesting results. While this might not necessarily improve your particular model it would be a way forward to do research on the algorithms used for one of your listed technological solutions to be able to improve its particular decision support capability.

Interview with Expert 4

Question 1: Do you believe the proposed model to be exhaustive?

Looking at the agriculture related challenges I would consider the list to be exhaustive. Especially the need for water and extreme weather and the related pest and diseases are significant challenges. Of course basic infrastructure is lacking in Africa as barely any farm has access to electricity or water pumps. I also appreciate your mentioning of missing financial support. Farmers in Africa have often times to access to financial markets that would allow them to take out cheap loans to conduct investments into their business.

I would also consider the mentioned technologies to be comprehensive. In fact I myself have made use of satellite imagery when I considered acquiring land in Senegal. I have also successfully used apps on mobile devices to detect diseases. As you already mentioned I would distinguish technologies based on their implementation effort which you have done by separating them into short- and long-term technologies.

Question 2: Do you consider the proposed model as useful and why (not)?

I think models like yours are useful but in my opinion technology can never 100 percent replace human skill. I believe an agronomist is always needed or at least will always be superior to any technology or app that is being developed. Your model can suggest that AI based technologies might have the potential to replace the agronomist but I believe the best way to leverage frameworks like yours is by developing a hybrid working approach.

One area that is being promoted by your model is the leapfrogging potential certain technologies pose. From personal experience I can say that every farmer in Africa has cell phone and many already own a smartphone allowing them to leverage disease detection apps. It was not predicted that farmers would own smartphones in areas without access to electricity and in the same way it remains unpredictable which technologies might be adopted next. We must also consider that most farmers would wish for a tractor and not advanced AI based technologies at the moment. However, we can already see that smartphone controlled solar powered irrigation systems are being used by African farmers and your model can contribute to the area-wide expansion of these systems by highlighting its impact as well as adoption requirements.

Question 3: Do you have any criticism against the proposed model?

My only critique would be that your model neglects that smallholders who make up 80 percent of all African farms need to increase their yield by a factor of ten to become profitable. This cannot be achieved by solely increasing the productivity but inevitably requires the expansion of farmland. However, your model tends to suggest that an improved yield per hectare could be enough. I do think this is needed as well but in combination with larger farm sizes.

Looking at the implementation steps you outlined I would argue that funding is not required. In fact most countries that have received funding from NGOs, the church, or the United Nations have not developed a sustainable agriculture industry. The support has resulted in a missing entrepreneurial spirit where the first question of a business talk is “where does the money come from” instead of how we can finance it and what the recurring cashflow would look like. Examples of such countries include Uganda or Burkina Faso. On the contrary, countries like Zimbabwe which have not received a lot of support from the international community due to political turmoil have developed into nations of entrepreneurs. Doing business with farmers from this region is professional and functioning co-operations can easily be established when negotiating with them on the same level. Coming back to my initial statement, what they need is not funding but access to bank systems and loans so they can finance their business themselves and take responsibility.

I do believe the points mentioned before are critical since smallholders are the future of African agriculture mostly because the political environment is too unstable to support the current dominance of large industrial agribusinesses with field sizes of several thousand hectares. In that sense allowing them to become profitable will allow the industry as well as a large share of the African population to develop.

Question 4: Do you have any suggestions on how to further improve the proposed model?

What I would add to your model is the need for private sector engagement to form co-operations with the farmers and thus, create sustainable business models. Furthermore, I would not mention the attraction of funding as a key requirement to adopt technologies but rather focus on access to cheap loans as a means to gain financial support. Moreover, the whole industry would benefit from a valorisation of the term “farmer”. They should be considered businessmen and put on the same level as engineers, doctors or lawyers. At the end of the day they make up the majority of the African population and develop its largest industry.

Interview with Expert 5

Question 1: Do you believe the proposed model to be exhaustive?

The agriculture challenges that you mention are all relevant in my opinion and no challenge comes to my mind that I would now not be able to attribute to one of the already listed categories. Similarly, the rather generally described technologies seem to be complete. I personally of course know most about satellite imagery since this is my daily business.

Question 2: Do you consider the proposed model as useful and why (not)?

We have tried to build a similar model like yours and failed because we did it in too much detail. You can make a table like yours for each technology you mentioned and dive deeper into the technologies. However, then it becomes quite the complex system and looses the purpose it was built for. Your model should highlight which technology can be used to deal with which agriculture related challenge and I believe it does exactly that without losing itself in detail. Additionally, it shows what steps need to be taken to adopt certain technologies and in my opinion even more important it shows which technologies do not require a comprehensive adoption plan.

I am most active in the satellite imagery sector and thus, can tell you that this is the most scalable technology. You can have drones fly over fields and they serve a very similar purpose and give more precise insights but are not scalable. I like how you show the difference between these technologies and what they mean in terms of adopting them.

Question 3: Do you have any criticism against the proposed model?

One point of improvement I have is the match between satellite imagery and precipitation patterns. It is possible to analyse soil with a depth of up to two meters by using satellite imagery and thus, capture soil moisture dynamics. This information can very well be used to highlight areas in fields that require irrigation.

Question 4: Do you have any suggestions on how to further improve the proposed model?

Even if this might be outside of the scope of your paper, I would like to see more level of detail regarding the technologies. For satellite imagery alone many differences exist. While these differences by no means do not change the outcome of your model, they could still very well be analysed individually.