Scouting the Autonomous Agricultural Machinery Market

Authors:
Jörg Dörr
Bob Fairclough
Jens Henningsen
Jasmin Jahić
Stefan Kersting
Patrick Mennig
Christian Peper
Friederike Scholten-Buschhoff

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Fraunhofer IESE is directed by
Prof. Dr.-Ing. Peter Liggesmeyer

Fraunhofer-Platz 1
67663 Kaiserslautern
Germany

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Kleffmann Group is owned by Burkhard Kleffmann

Mühlenstraße 1
59348 Lüdinghausen
Germany

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1 Objectives of this Study and Approach

In the agricultural domain, practitioners as well as researchers work towards the development and validation of agricultural machinery with autonomous functionality. There is currently a strong debate on what autonomous machinery might look like in the future, how the market will develop, and which factors will influence the development of autonomous machines in the agricultural market.

This study contributes to this discussion by scouting the autonomous agricultural machinery market. The goal of this study is not to provide a complete market forecast, but to identify relevant factors that will influence the development, estimate their importance, understand the biggest uncertainties, and get a feeling of the state of the practice and the state of the art, as well as on how the experts see future developments. This study is relevant for practitioners (farmers, agricultural machinery companies, smart farming players) as well as researchers in the field of agriculture and autonomous systems. It also serves as a starting point for further in-depth studies.

In order to determine the results of this study, Fraunhofer IESE and the Kleffmann Group used a hybrid approach. On the one hand, comprehensive desk research was conducted. On the other hand, a series of interviews and workshops took place to elicit expert opinions.

The goals of the desk research were:

- Identification of technological and market influence factors (see chapter 2)
- Gathering of information for market development (see chapter 4.1)

This documentation includes an excerpt of the main findings of the desk research results.

The goals of the expert involvement, which included interviews and workshops, were:

- Elicitation of expert opinions on the relevant influence factors (see chapter 2)
- Elicitation of expert estimations on how the different levels of autonomy will develop in terms of market shares within the next 25 years (see chapter 4.2)

For this purpose, a total of fifteen experts[1] from various domains contributed to this study. We involved experts from

- Classical agricultural machinery
- IT solutions in Smart Farming
- Researchers in Smart Farming and Autonomous Systems
- Legal issues in the agricultural domain
- Agricultural press

The experts were assured strict anonymity and were asked to express their honest opinions and give unbiased estimations.

Furthermore, Kleffmann Group conducted statistical modeling based on historical tractor sales data and FAO projections to quantify the market development until 2045. The quantitative modeling focuses on scouting how the markets could develop in the next 25 years based on the information obtained from the desk research and the expert assessments (see chapter 4).

[1] As can be seen from the number of involved experts, this study was not aimed at performing a representative survey with quantitative numbers, but rather at getting a qualitative estimate from renowned experts in the field.

2 Description of Main Influence Factors: Enablers and Inhibitors

In order to enable autonomous systems and related use cases, there exist various factors that influence how autonomous processes in the agriculture sector will develop in the future. We distinguish these into (1) technical factors, such as development of sensor and actuation technology, and pattern recognition technology and (2) market factors, such as climate change, demographic change, and consolidation in the agricultural industry. All these factors will enable or inhibit the future development of autonomous systems in the agricultural market. In this section, we will discuss in detail how we see the development of these influence factors in this domain. At the end of this section, we will discuss contradictory predictions from the state of the art and the interviewed experts and prioritize the influence factors as seen by the domain experts.

Techno-logy-related influence factors	Sensors and Actuator Technology
	Pattern Recognition
	Decision Making Process
	Complexity of Autonomous Actions
	Standards
	Laws and Legislation
	Trust and Acceptance
Market-related influence factors	Change of Climate and Natural Conditions
	Consolidation in the Agricultural Industry and Change of Food Production Systems
	Farm Productivity and Profitability
	Demographic and Social Change
	Political and Economic Framework
	Regulatory and Pest / Disease Pressure

Figure 1 The main factors influencing autonomous systems in agriculture.

2.1 Technology-related Influence Factors: Enablers and Inhibitors

2.1.1 Sensor and Actuator Technology

Autonomous machines rely on sensors and actuators to engage with their environment. To determine the state of the machine as well as the state of the field or crops, autonomous machines use various sensors. Their input is processed in hardware and software to generate decisions and control actuators. Apart from regular challenges faced by autonomous vehicles (e.g., changing weather conditions), autonomous agricultural vehicles face additional challenges such as mud and dirt blocking optical sensors or ground conditions being substantially worse than for autonomous cars.

Sensor and actuator technology in the area of autonomous operations have seen significant developments in the past. Sensors, which are crucial for pattern recognition and for providing enough information for decision-making, are expected to provide enough information about: i) the machine itself; ii) the intermediate field area of operation; and iii) overall field information. The Global Navigation Satellite System (GNSS) [1] is widely used in agriculture. There already exist approaches for utilization of aerial and ground-based platforms for crops scouting [2] [3]. They enable precision farming – detailed information for decision support, with minimal user intervention. In addition, they help to bridge the sensing gap as they use unmanned aerial vehicles (UAV) for monitoring the fields with a relatively high level of detail, without having to rely on a machine driving in the field. This enables robust perception for on-field operation. In terms of concrete use cases, UAV enables weed detection, subsequent control measures in the field, detection of crop nitrogen status [4], and site-specific precision management.

Optical sensing provides a cost effective and rapid technique for the measurement of biophysical and biochemical status of plants [5]. Such sensing:

- is based on measurement of compounds such as chlorophyll
- covers electromagnetic spectrum sensing techniques
- provides remote (e.g., using airborne or satellite platforms) sensing techniques

3D imaging of crops using, for example, LIDAR, stereo cameras, or time of flight (TOF) [5], can provide physical or structural information and attributes regarding plants:

- High throughput screening
- Plant phenotyping for breeding
- Normalizing of measurements from other sensors

Most optical sensing mechanisms (e.g. hyperspectral analytics, spectroscopy [6]) can also be applied to machine vision [5] to cover visible and near-infrared ranges. Imaging has advantages over sensors:

- Cameras deployed on remote platforms (UAV) can be used to capture canopy reflectance or thermal measurements with full field coverage at high spatial resolution
- Ground-based machine vision sensors can better isolate soil influence on the signal by first segmenting leaves and plants within the image,
- The image resolution offered by cameras can also be used to resolve structural information at the plant and leaf level that could be utilized for nitrogen management of the crop

Below, we list some existing, but still futuristic, sensor and actuation techniques:

1. Soli [7]: ubiquitous gesture sensing with millimeter wave radar. This technique, published in 2016, functions as an input device (Figure 2). It uses near-field robust gesture recognition with sub-millimeter accuracy and can be used for very detailed gesture input. It is part of the next Pixel smartphone to be released in 2019.
2. RESI [8] is a wearable computing sensor for interactive textiles. It is used for pressure sensing, e.g., in gloves for telepresence or, for in-seat interfaces.
3. Tacttoo (Figure 3), a Thin and Feel-Through Tattoo for On-Skin Tactile Output [9], is an on-body interaction sensor. It is used for tactile display and implemented with printed electronics and wearable computing. Its potential is in augmented reality on physical 3D models, alignment with real-world and virtual tactile stimuli on physical objects, and augmented surfaces (paper, fabrics, machines, etc.). One of the applications is to control machines (e.g., directly by touching certain areas of the body without looking away from something).
4. SwarmHaptics (Figure 4): Haptic Display with Swarm Robots [10] tries to answer the question of: what can be done when we have a swarm of small miniature robots that can interact with humans and vice versa. This device can have possible applications in swarm robots to convey information, notify users, or let them interact with systems. It could be used for farmer training when working with future swarm robots.
5. Feel the noise [11]: mid-air ultrasound haptics as a novel human-vehicle T interaction paradigm. It represents an evaluation of typical touch interfaces vs mid-air gestures supported by haptic feedback through ultrasound. It could be useful for transferring haptic information from ground sensors to the cabin.

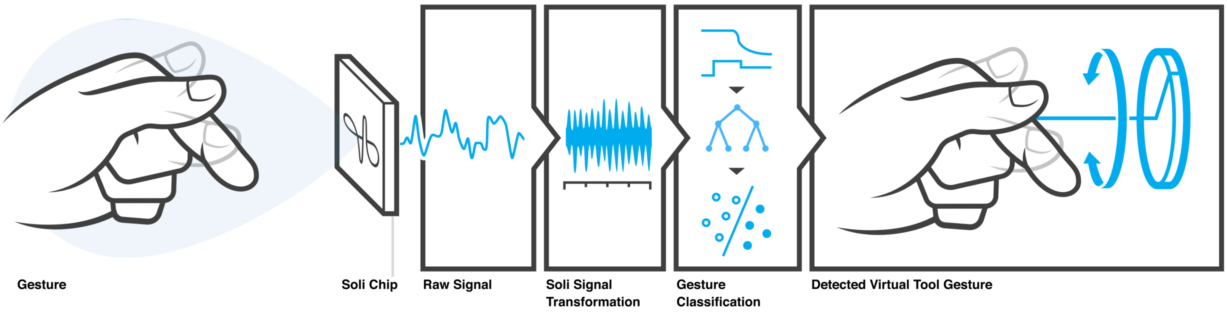

Figure 2 Illustration of the Soli approach [7].

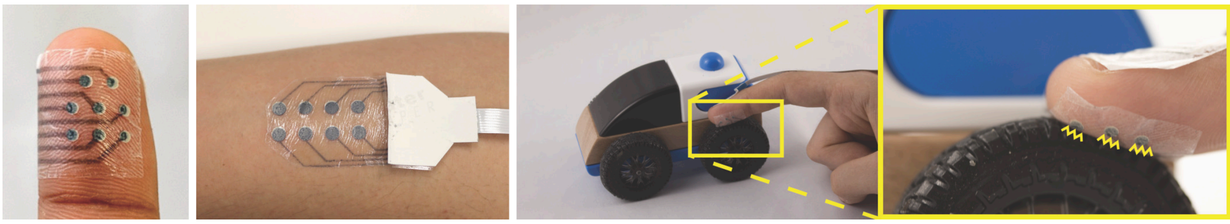

Figure 3 Tacttoo - A thin and feel-through tattoo for on-skin tactile output [9].

Figure 4 SwarmHaptics: Haptic display with swarm robots [10].

Experts state that although such automation solutions have been around for some time now, they are not used everywhere. Machines today need more sensors to achieve autonomy. However, the bigger problem is that machines today do not use the sensors that already exist. Such solutions are preconditions for autonomous agricultural processes and for the development of autonomous systems. Experts claim that there are still challenges in transforming environmental factors (e.g., weather, soil properties, and plant dieses) into a digital form. The agricultural environment is a multi-functional system. If one condition changes, the whole system can potentially change. Currently, farmers are still struggling with understanding existing sensor data. Today, the farmer's own opinion is still the most important input, and sensor inputs are considered as second or third opinion.

Robotics opens up the potential for mass direct in-field phenotyping of crops under realistic farm conditions. Small, smart, electric robots provide an alternative solution to the existing solutions that require a lot of energy, by avoiding excessive compaction of the soil in the first place and performing micro-tillage using on-board implements [12]. Current fruit harvesting robots can pick one strawberry every two seconds (= 30 per minute; humans pick 15 or 20 per minute) [4]. The prediction is that supervised groups of robots can replace strawberry pickers in around five years. In the future, UAV, in combination with sensors, will enable continuous collection of field data [3] [4].

Experts claim that in the near future, sensors are still more likely to be seen as helping farmers to sharpen their view. In the future, there will be a great need not only for sensors that gather more information and for sensing types, but also for the interpretation of sensor data so that farmers can understand it (as if they were in the field). Most of the technologies today originate from other industries and are usually adapted for agriculture. In the future, this needs to change.

2.1.2 Pattern Recognition

The first challenge that autonomous agricultural processes need to solve is to identify objects in, and properties related to, the field (based on their patterns). The primary pattern of interest are crops, where the main task of pattern recognition lies in differentiating the crops from their surroundings (e.g., recognizing corn and separating it from weeds). Other patterns directly related to autonomous agriculture are patterns related to pests and obstacles in the field. Patterns with secondary significance to be recognized are related to field properties (e.g., nutrition value and moisture of certain areas), environment (e.g., weather conditions, rain prediction), and crop properties (e.g., ripeness of crops, healthiness of crops).

Regarding this track, there exist several studies. Kiani and Jafari [13] performed a study on crop detection. They showed that using only 180 images (for neural network training [13]) consisting of corn plants and four species of common weeds under normal conditions in the field, they were able to distinguish corn plants with an accuracy of 100 % while at most 4 % of the weeds were incorrectly classified as corn. The high accuracy of this method is due to the significant difference between corn and weeds during the critical period of weeding in the region. Other examples of distinguishing crops from their surroundings include detection of broad-leaved weeds [14], shape features of the radish plant and weeds [15] (the success rate of recognition was 92 % for radish and 98 % for weeds), and sugar beet weed segmentation [16] (with a classification success rate of up to 96 %). Approaches existing today for obstacle detection in autonomous driving use obstacle-pattern-recognition algorithms in combination with simulated virtual sensor networks [17] [18]. Under regular weather conditions and under the assumption that the objects of interest are significantly different from their surroundings, these pattern recognition algorithms perform well, with high accuracy [13]. When it comes to the identification of properties of field and crops, pattern recognition can contribute to solving problems such as water shortage or pests. A study by C. Bauckhage and K. Kersting [19] focuses on these problems. They presented a case study that surveys existing developments in these areas and they concluded that methods from the field of artificial intelligence (AI) (e.g., pattern recognition) can contribute to solving problems due to water shortage (e.g., dry stress) or pests by detecting such regions and infected plants in real-time.

The experts also agree with scientific conclusions that the differentiation between crops and their surrounding is already possible. They point out two approaches for this: i) camera technology that recognizes the row structure, and identifies the patterns; and ii) camera technology that relies on self-learning from pictures, where an AI recognizes the structure from pictures.

At this point in development, artificial intelligence based on supervised learning remains the most significant technology for pattern recognition. There are no significant research efforts to replace artificial intelligence as a key technology for pattern recognition. Ongoing research focuses on understanding supervised learning and making it faster and more reliable, while trying to quantify its precision. There are some efforts, in the automotive industry to combine artificial intelligence with classical algorithms in order to provide certain safety guarantees.

Experts point out a challenge in pattern recognition under changing environmental conditions, which affects the precision of pattern recognition. Humans currently have the advantage of adaptability (e.g., to the conditions of the environment) over machine systems, which are still rigid. Furthermore, machines must have appropriate sensors to perform pattern recognition for any type of object or phenomenon. These challenges are expected to be resolved in the future.

2.1.3 Decision Making Process

Autonomous vehicles constantly try to answer three questions [1]: i) Where am I? ii) Where am I going? and iii) How do I get there? The decision-making process that answers these questions considers the execution of perception and action functionalities [1] (Figure 5). Perception is closely associated with safety properties, and the whole process is under the influence of external factors (e.g., mission description) as well as the environment and the platform of the robot.

When it comes to making decisions, the process is heavily dependent on the operation type in autonomous vehicles and on the type of the autonomous system itself. Some decisions in agriculture have been automated for a long time. For example, transmission technologies and advanced steering control systems (e.g., drive-by-wire) [20] are standard in modern agriculture. Tractor guidance and steering control technologies have been in commercial use, in different stages of autonomy, for two decades [21]. In addition, a number of systems have been developed that automatically optimize machine performance. However, making decisions about routing and collision avoidance in unstructured, dynamic, open-ended and weather influenced environments [1] remains a challenge [21]. Continuously changing conditions and variability in environments [22] contribute to the complexity of the issue. Some researchers claim that the main reasons for this is a lack of an appropriate and commonly used open software platform for precision agriculture, which would decrease development time and enable reuse of existing work (localization, mapping, path planning) [1]. Although many platforms and toolkits that support decision-making processes already exist (e.g., CARMEN Robot Navigation Toolkit [23], CLARAty (Coupled Layer Architecture for Robotic Autonomy) [24], MRDS (Microsoft Robotics Developer Studio) [25], ROS (Robot Operating System) [26], Orca and Orocos [27] [28], Agroamara [29], Mobotware [30], FroboMind [1]), there is still a need for a unified platforms that will bring researchers and practitioners from different fields closer.

Future technology is expected to benefit from pattern recognition using artificial intelligence (e.g., Deep Learning to interpret all the data from a color camera fast [4]). Cloud-based farm management platforms already exist to some extent. In the future [20] [31], they will aim to integrate data from multiple sensors, vehicles, weather, and other sources across different manufacturers. Also, by including decision support systems, they will be able to provide a more versatile data infrastructure in the future.

Experts and researchers agree that systems of multiple robots are expected and needed in the future [31] (e.g., machine-to-machine communication, telematics, infield communication, data infrastructure for more sophisticated autonomy and decision support). More robust, reliable information-acquisition systems, including sensor-fusion algorithms and data analysis, should be suited to the dynamic conditions of unstructured agricultural environments [32].

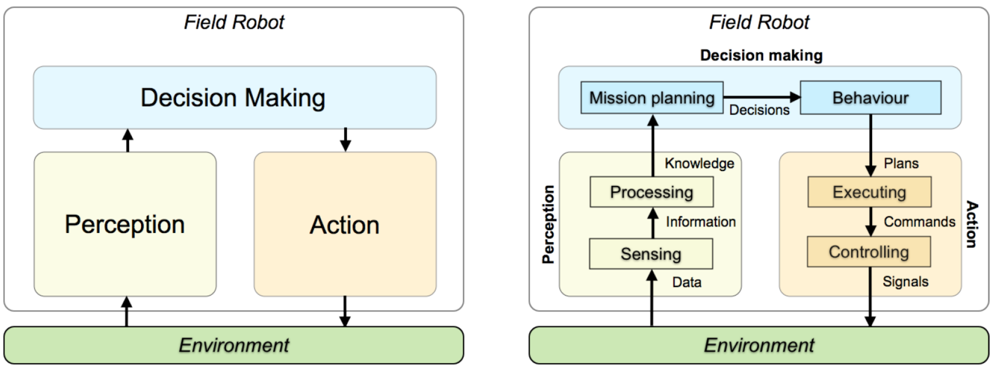

Figure 5

Decomposition of an Artificial Intelligence agent [1]. (left) The agent perceives its environment through sensors and acts through actuators. The action taken by the agent in response to any percept sequence is defined by an agent function. (right) Decomposition of (left).

2.1.4 Complexity of Autonomous Actions

The desired goal of autonomous operations is to work in unstructured agricultural environments with the same, and even better, quality of work achieved by current methods and means [22]. Complex autonomous actions include actions in the field (e.g. yield monitoring, yield mapping, variable rate application, which are already automated [2] [33]), guidance technologies [21], path planning and route optimization, and functional control aspects [21].

There is a number of sensing products that support crop management (i.e., process monitoring) [31]. Examples of other existing agricultural operations include: auto-steering, auto-seeding, selective weed picking [34] [35], yield estimation [36], irrigation [37], and harvesting [38]. Scientific prototypes of many individual technology solutions exist [22] (e.g., information-acquisition systems, sensor fusion algorithms, data analysis). However, they represent only pieces in a complex challenge. Fully autonomous solutions for the previously mentioned complex actions are not yet available commercially. Requirements for future autonomous operations include [22]: cost-effective, safe, reliable in terms of human safety, preservation of the environment, the crop, and the machinery. Factors limiting commercialization of existing solutions are: poor detection performance [32], inappropriate decision-making [32], low action success rate [32], and lack of economic justification. It is expected that economic justification will change as technologies offering such solutions become progressively more affordable [20]. In addition, increased production is currently required to make Automated Robotic Systems (ARS) economically justifiable [20].

Experts agree that autonomy in agricultural operations requires significant improvements. In particular, the data infrastructure must be further developed to support complex autonomous actions. Innovative technology is expected to be increasingly developed for use in the machines (e.g., tractor), but also in the implements. According to the current state of the practice, experts point out that the intelligence on the tractor is rather being developed by independent companies and not necessarily by the manufacturers themselves. The current state of development is 80 % old machines and 20 % new machines. The new models are more likely to be found within the scope of machinery rings, contractors, and large farms. The driver for the current state of development is the consolidation of agriculture in Europe.

In order to enable the execution of complex actions in an autonomous manner, researchers agree that system sizes should be reduced while improving the integration of all parts and components that solve individual, smaller challenges [22]. The further integration of all such sub-systems is expected to enable sustainable performance and fully autonomous complex operations [32].

According to experts, the first phase of development of autonomous solutions for complex actions will consider the involvement of farmers in the form of driver-led and assisted driver-led operations. In the near future, farming operators are expected to still occupy the vehicle. In the second stage of autonomy development, it is assumed that, for performing complex actions, farming operators will be able to leave the vehicle on the field and take over the role of an online operator. In this stage, a farmer can will be able to look after two to three machines that driving alongside each other (master-slave mode). In the final stage of autonomy, which experts believe to be inevitable, farmers will still play a part in the process, but mainly for monitoring tasks. It is expected that, in this phase, machines will be able to perform actions autonomously and potentially decide when and what actions to take (e.g., when to go out, which crop to protect).

2.1.5 Standards

Autonomous driving is a safety-critical operation. In a broader context, besides safety, the scope of autonomous driving also includes remote surveillance and control, with the emphasis on machine-to-machine communication and human-to-machine communication. Because standards enable interoperability among different machines and implements, it is expected that they will prescribe definitions for the reliability and security of communication for this domain.

The most well-known standardization efforts are the following:

- Machine-to-Machine Communications: The communications standard [20] ISOBUS is for standardizing farm equipment that creates and handles farm data. The ISO standard 11783 defines serial control and communications data networks for tractors and agricultural machinery. In order to achieve a large degree of autonomy, data produced by agricultural vehicles must be processed and reasoning needs to be performed. Such data might first be sent to the cloud infrastructure of the respective manufacturer before it is then shared between different clouds through standardized interfaces, semantics and data structures.
- SAE J3016: Taxonomy and Definitions for Terms Related to Automate Driving [39] defines terminology around automated driving such as automation levels.
- UL4600 – Standard for Safety for The Evaluation of Autonomous Products [40] provides a set of normative requirements on how to build a proper safety case for autonomous systems. The scope of this standard is mostly on autonomous driving with a focus on what things need to be assured. The standard is scheduled to be released in 2020.
- SOTIF – Safety of the Intended Functionality [41] deals with assuring the absence of unreasonable risk due to hazards resulting from functional insufficiencies of the intended functionality or from reasonably foreseeable misuse by persons. Practically, this refers to creating sufficient situational awareness and is targeted at finding problems induced by the incapability of sensors and

sensor fusion to properly determine relevant properties of the environment. SOTIF is a very important standard for complex decision logic relying on complex situational awareness. As of its 2019 release, it deals only with automation levels L1 and L2 (according to SAE J3016 automation scale) explicitly, but the working group is currently extending the standard up to level 5 (highest level of driving automation).

Experts mentioned homologation[2] of agricultural machinery. There are no uniform standards, especially in the field of implements, and accordingly there are many different requirements in the individual countries that manufacturers have to fulfil. Experts believe that this would lead to similar challenges in robotics and consequently to high costs.

There will be a great need in the future for the standardization of terms, system-performance measures and methodologies for comparing robot performance and technical progress [32]. Open data standards for communication between the vehicle (implement) and management software are urgently needed, and it is expected that most, if not all, manufactures will subscribe to these standards [20].

Experts particularly emphasize the role of security in the working process of autonomous vehicles and see it as a great obstacle to further development in this area.

2.1.6 Laws and Legislation

Vehicles can cause damage to property and even lead to the loss of human lives. Before adopting autonomous operations, it is primarily necessary to define laws and legislation regarding liability of autonomous machines and their manufacturers. Besides liability laws being enacted, insurance companies must also offer appropriate packages. As a side effect, autonomous systems inheritably produce a significant amount of data and perform actions that are subject to various agricultural regulations (e.g., CO_2 emissions, usage of fertilizers). Currently, farmers are worried about how this data will be used.

Researchers mostly discuss the existing challenges in the area of autonomous operations in terms of ethical decisions made by the artificial intelligence [43], responsibility for hazards that could occur [44], and ownership of data (closely related to privacy) [45] [46]. They notice that some markets are far ahead of others in the discussion on autonomy.

[2] "Homologation is the process of certifying or approving a product to indicate that it meets regulatory standards and specifications, such as safety and technical requirements" [42].

Experts emphasize that the current state of legislation related to the agricultural machinery market is complex and in need of improvements. This is especially a challenge in the field of the innovations that autonomous farm systems introduce. Traffic laws that should be addressed and updated in this regard are related to: i) road traffic, ii) liability and iii) criminal justice. When it comes to laws regarding operations in the field, liability law cases should be established related to field damage, game damage, and damage to the associated equipment and property. Today, insurance companies are only willing to cover personal risks. In order to approve autonomous systems on the road, it is necessary that insurance companies also cover the system and the consequences of the operations of such systems. Accordingly, the experts argued to distinguish between on- and off-road operations and to separate these two areas in order to create corresponding legal regulation. Experts also point out that the approach to such laws varies greatly from region to region. For example, North American laws are very liberal from the product approval point of view and therefore autonomous systems have a higher chance of being used there. In China, the government can enforce certain laws and procedures and put them in motion in practice much faster than in the rest of the world. Experts also agree that the EU is stagnating in this field, although they see the potential that, in the case of a change of policies, the EU could play a pioneering role in defining a legal framework. The European Union has well-defined laws about agriculture (e.g., fertilizers, pests, pesticides), which can be a basis for the further development of laws. Africa and South America, on the other hand, are difficult to assess.

Finally, there is a concern about the data produced by autonomous systems. The question is who owns the data of such machines. This challenge remains unsolved today.

Both experts and researchers agree that some markets are far ahead of others in the in the discussion of autonomy on the legal level. For example, Australia is already quite autonomous. USA and Australia are therefore predicted to become the trailblazers (2035). It is supposed that by 2045, autonomy will be present in Asia and Africa as well.

Experts point out that it is very hard to predict how the legal situation will develop in the future (e.g., in the next 20 years). One of the reasons for this difficulty to predict future development is the number of stakeholders (e.g., software developers, machine manufacturers, field owners). They agree that no regulations (or their lack) will be able to stop innovations (although this could slow down their acceptance). The only question is where innovations will emerge first. Some experts believe that limitations should be imposed by road traffic regulations, which could solve most of the problems.

2.1.7 Trust and Acceptance of Autonomous Technology

There exist strong social relationships between farmers and their close associates [47]. Therefore, it is important to reason on whether AI can replace the existing social relationships: i) Does the farmer spend as much time with the AI asking questions, being skeptical, wondering about this and that? ii) Does the farmer trust the AI with their fears and longings? iii) Does the AI care about the farmer as a person? If AIs do not care and farmers do not really trust them, then there is a great risk when replacing humans with artificial systems.

Operators in the area of agricultural machinery require trustworthy systems. Trust that a system inspires is characterized by [47]: i) competency (skills, reliability, and experience) and ii) Integrity (motives, honesty, and character). If an autonomous system lacks competencies, it might still have the high integrity. However, if it starts behaving mysteriously (e.g., if the collected data is unavailable), it loses its integrity. Such behavior might result from machine learning algorithms that direct the robot to act in ways confounding to the human operator (the human might wonder why this robot is acting in this way) [47]. According to a study by Devitt (2018), reasons for not adopting driverless tractors, agricultural crop picking robots, and UAV's are: i) inability to generate trust; ii) loss of farming knowledge; and iii) reduced social cognition [47]. The higher the autonomy, the less a human needs to operate. The less a human needs to operate, the less aware they are of on-farm activities, which in turn may affect strategic decision-making about the enterprise [47]. A loss of farming knowledge [47] occurs as machines take over a range of operations. A high level of automation brings cognitive risks regarding enterprise perception, knowledge and understanding. The main challenge for an autonomous system is therefore to gather information at the same level of granularity that farmers can gather while driving their tractor on the field. This includes sight, sound, smell proprioception, and touch. The question here is also whether there is a need for farmers to go to the field. If yes, then they will need a vehicle to take them there. If farmers do not directly perceive their own farm and create sophisticated knowledge representations, they may struggle to imagine or plan possible future actions on their farm in a meaningful way. Sometimes data collection does not resonate with farmers and they can plan better if they go across the field.

Experts claim that acceptance of technology depends in large part on the awareness of people about the technology. While in some areas (e.g., North America) a technology may be widely accepted, in other areas (e.g., South-East Asia) farmers might feel reluctant to accept the new technology as it disturbs their traditional way of doing agriculture. Today, there is great social pressure to automate certain tasks that humans do not want to perform anymore.

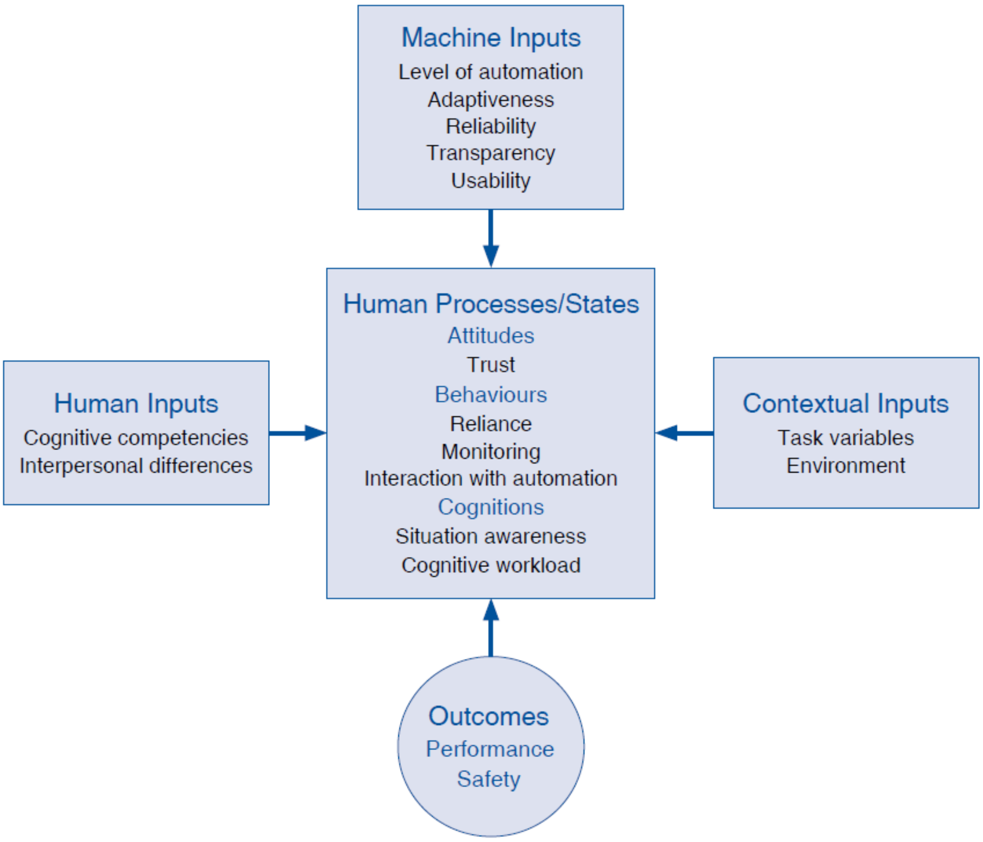

Figure 6 Framework of factors affecting safety and performance in human-machine systems [47].

The phases of autonomy being adopted agriculture [47] mainly include: i) user adoption, where the barriers are the cost of technology and the lack of belief that the technology will be an overall advantage; ii) initial use, where the barriers are the calibration to individual farm parameters (e.g., GPS coordinates, soil, water, crop type, seed type), personalization to individual farmer needs and preferences (e.g., speed, accuracy, level of detail), and learning (e.g. experimentation, workshops, product manuals, personal assistance); and iii) post-adoptive use, with the main barriers being the failure of the technology to adapt to changing user needs and poor support services to help users use the product or maintain the technology when it needs servicing or repairs.

Experts predict that in the future, we will see the changes in the farmer's role in agriculture, who will gradually shift from being an operator to being a supervisor (e.g., to doing only monitoring jobs). It is expected that integration of human operators into the system control loop for increased system performance and reliability [22] will take place first. This will be followed by efforts to move the farmer farther and farther away from the field. During this process, the technology will have to ensure that the farmer gets reliable information from the field, and the autonomous actions have to be good enough that the farmer will trust them.

2.2 Market-related Influencing Factors: Enablers and Inhibitors

The market for autonomous agricultural machinery is driven partly by technological progress (as described so far) and partly by the demand for such machines. While the technological enablers mentioned above primarily determine the availability of such autonomous machines, the demand, generated by farmers, is driven by a range of structural, social, political or economic influences all of which have a potential impact on demand [48]. If we look outside of the realm of agriculture, we find numerous examples of where "superior" technologies that were "ahead of their time" (including, for example, both Betamax and Palm) failed to succeed commercially as a result of "market related factors despite being technologically advanced" [49]. The following section outlines what can be considered as the most influential market related factors impacting the market for autonomous agricultural machinery.

2.2.1 Change of Climate and Natural Conditions

Climate change can refer to changes in weather, climate variability, or indeed actual climate change itself. These three phenomena work on different time scales, and while all have the potential to affect the market for autonomous agricultural machinery out to 2045, climate variability and climate change will be the more significant ones the years to come. Weather includes current atmospheric conditions such as rainfall, temperature, and wind speed, which occur at a particular place and over periods of hours, days, or months. Climate variability occurs over longer time spans, like years or decades. This includes weather phenomena such as El Niño or La Nina, which on a regular basis cause a reversal of wind patterns across the Pacific, drought in Australasia, and unseasonal heavy rains in South America. Climate is the average weather pattern for a particular place over several decades.

At first glance, the direct impact of climate change on the market for autonomous agricultural machinery could be considered to be only of minor importance. However, combining both its direct and indirect impact, climate change has the potential to alter agricultural production conditions in some parts of the world. Unfortunately, however, there is no universally accepted outcome of the impact of climate change out to 2045, with many projections & models providing different outcomes [50].

If, however, we were to assume even a modest global warming of +1 °C over the next 25 years this would lead to (among other weather phenomena):

1. Precipitation volatility leading to floods (as in India in 2019 and the US in 2019) and droughts (as in Australia since 2017)
2. A decrease in available arable land as a result of soil erosion, as for instance in the US [51]
3. A noticeable quality impact (and subsequent nutritional impact) as well as quantity (yield) reduction in most parts of the world [52]

Climate change will affect every aspect of food production with regional differences becoming very noticeable. In its latest assessment, the IPCC (Intergovernmental Panel on Climate Change) stated with high confidence that in low-latitude countries, crop production will be 'consistently and negatively affected by climate change'. In northern latitudes, the impact on production is more uncertain; there may be positive or negative consequences.

While the direct impact of climate changes on the developmental progress of autonomous agricultural machinery is in very general terms incremental and generally predictable (dependent upon actual changes), the indirect impact is far more difficult to quantify. Although various indirect impacts could be discussed, one of the chief ones is the requirement under the Paris Agreement on Climate Change (UNFCCC, 2015) to reduce greenhouse gas (GHG) emissions. Over the past 50 years, GHG emissions resulting from agriculture, forestry and other land use have nearly doubled, with projections suggesting a further increase by 2050 [53]. The agricultural sector produces an estimated 21 % of total global GHG emissions and as such is a key target area for reduction. A further negative flipside is that agriculture is estimated to be the proximate driver for around 80 % of deforestation worldwide. Forests are one of the natural carbon sequesters, so meaning they reduce global GHG levels, and deforestation then aggravates the problem. These two negative consequences of GHG emissions are indirect aspects of agriculture, often more associated with modern intensive farming methods rather than extensive farming, which will potentially impact the market for autonomous agricultural machinery.

2.2.2 Consolidation in the AG Industry and Change of Food Production Systems

Farms are becoming fewer in number and larger in size. In the EU for instance, the average annual rate of decline between 2005 and 2013 stood at 2 % for the EU-27, with greater losses in the countries that joined the EU in 2004 and 2007 (EU-12: -2.7 % per year) than in the older Member States (EU-15: -0.9 % per year) [54]. In the US, the consolidation of farms is even more marked, with the USDA Census of Agriculture results showing a drop in the number of farms from 2.13 m to 2.03 million over the period of 2011 to 2018 and average farm size increasing from 429 acres to 443 m acres [55].

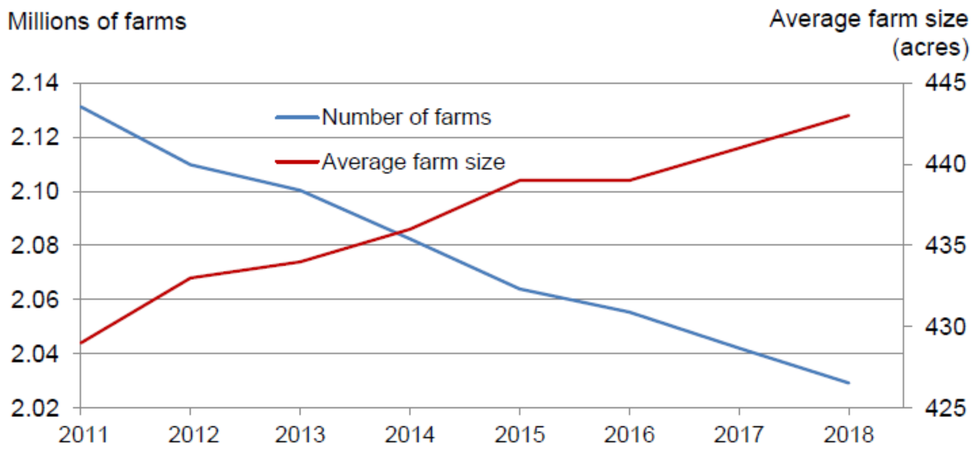

Figure 7 Number of Farms and Average Farm Size – United States: 2011-2018 [55].

Broadly speaking, this pattern is replicated around the globe, although much slower in developing nations in Asia and Africa than in the developed regions of the world. The drive to larger farms is essentially aimed at productivity improvement and "economies of scale", which is proven to be the case, for example, in the US; but there is much debate among productivity economists for example in China [56]. In the conventional development paradigm, farmers who remain in the sector change their practices, shifting from multiple crops to monoculture, and moving away from staples toward higher-value foods and cash crops. Risks that were previously pervasive are managed better, and the impact of shocks is covered by insurance. Inputs previously produced on-farm and most food items for the farmer's family are increasingly bought through markets. Gradually, farmers are able to integrate into commercial food systems, earning higher incomes and employing better technologies. Clear modifications that form part of larger farm practices include:

1. Change in land use, e.g., a shift from non-arable cropping towards arable and vice-versa, in part dependent on policy
2. Continual trend towards non-till and low-till agriculture as in the US
3. Increase of agricultural productivity due to adoption of new technologies

The speed and patterns of consolidation differ across regions and, broadly speaking, the point on the "consolidation road" where each region is currently at differs significantly, as indicated in Figure 8.

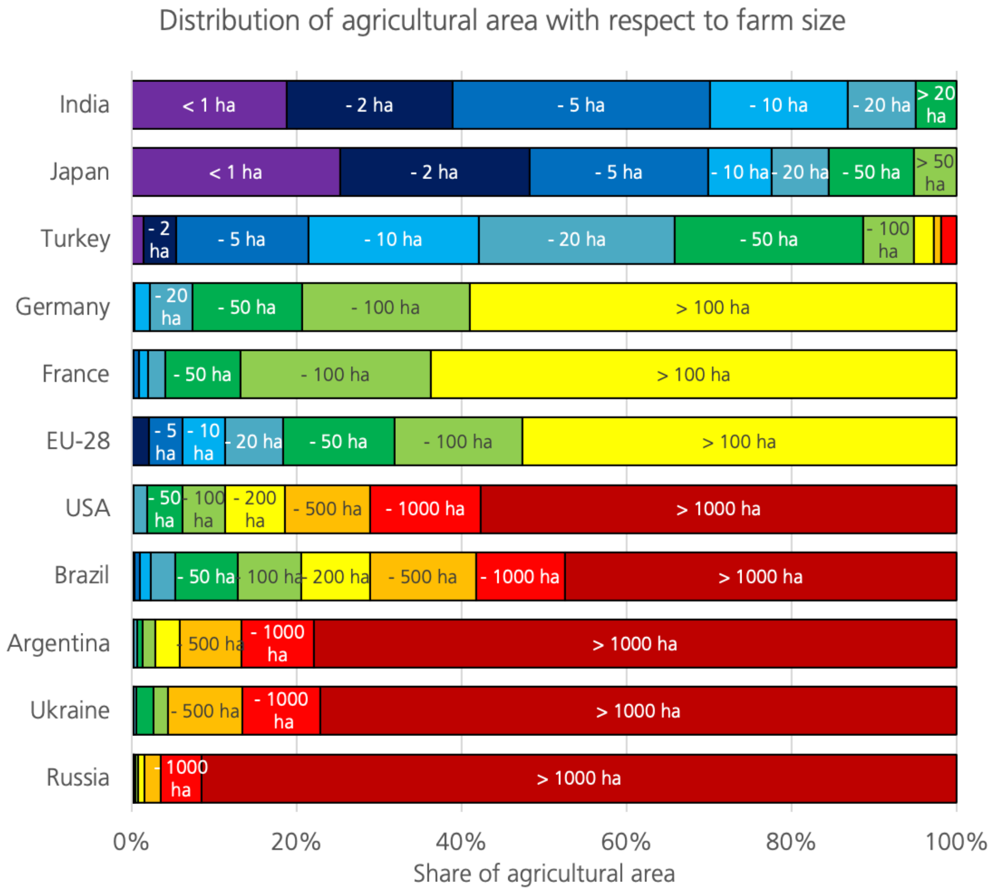

Figure 8

Distribution of agricultural area according to farm size in different countries. Based on latest available data provided by FAO [57], EUROSTAT [58] and various national agricultural censuses.

The final impact of larger rather than small farms on the market for autonomous agricultural machinery depends upon many factors. Not the least of these is the point on the "consolidation road" where any given farm is; as a driver going forward, its impact is very likely to be significant. Moreover, the differences in farm structure are expected to be one reason for the emergence of regional differences with respect to the uptake of autonomous agricultural systems.

2.2.3 Farm Productivity and Profitability

To meet demand, by 2050 agriculture is expected to need to produce almost 50 % more food, feed, and biofuel than it did in 2012. This FAO estimate takes into account recent United Nations projections indicating that the world's population would reach 9.73 billion in 2050 [59]. Given that yield increases are slowing and yields of major crops vary substantially across regions, increased farm productivity and profitability are one key route to meeting this demand. Farm profitability (and productivity in turn) is, closely linked to commodity prices [60].

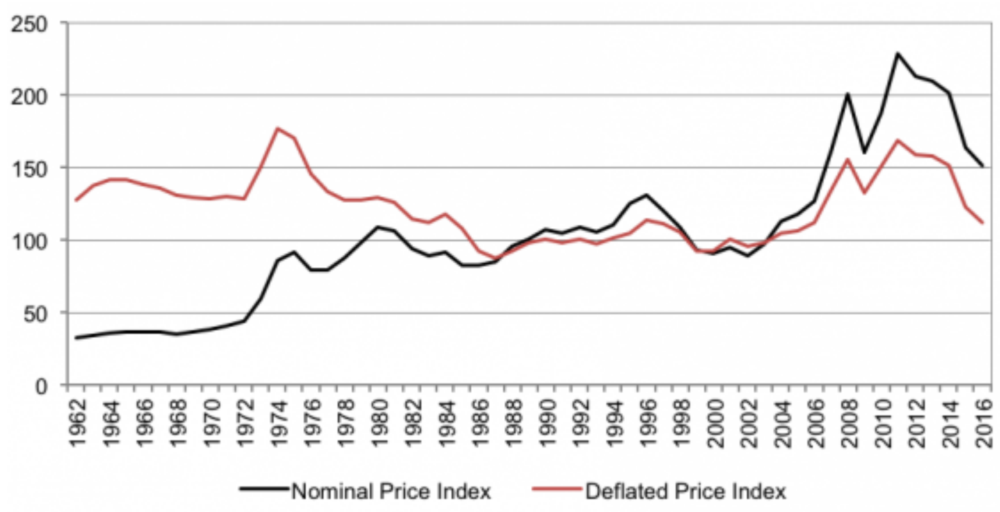

Figure 9 Development of nominal and deflated price indices [61].

Generally speaking, commodity prices have been particularly volatile over the past decade, with a number of significant peaks and troughs characterizing price trends for the basket of core food commodities that is tracked by the UN's Food and Agriculture Organization (FAO). After an extended period in which real food prices mostly exhibited a downward trend, prices rose sharply in 2006/07 and again in 2010/11. During the financial crisis in 2008/09, in contrast, food prices dropped dramatically at the same time as output slowed in several major economies. The trend since 2016 has also been one of decline both in nominal terms and in real (deflated price index) terms, driven largely by the impact of growing protectionism in agricultural trade and in particular between China and the USA.

Looking forward, the most recent joint report by FAO and the Organization for Economic Co-operation and Development (OECD) provides a somewhat mixed picture of medium-term developments in real food commodity prices to 2025. While the prices of meat and cereals, with the exception of coarse grains, are projected to decline in real terms, prices for dairy products will tend to rise over the next ten years. While prices are generally projected to remain structurally higher than in the decade before the 2007–2008 price spike, such medium-term developments are 'not inconsistent with a very long-term trend for declining real prices' [62].

With a slowdown of economies and no immediate long-term solution to policies increasing protectionism in agricultural trade, all indications are for a long-term trend of price decline. Offsetting this to some extent will be a modest increase in direct subsidies and government support driven in some countries by a need to mitigate protectionism policies as well an increase in "greening policies", where farmers are paid for practices that benefit the environment rather than for the production of commodities. Other factors that might also slow down the expected decline of commodity prices in the long-term are climate change and limited production resources. Both factors can jeopardize the increase in agricultural yield that is necessary to meet the increasing global food demand. If the supply of food cannot keep pace with the demand, this would result in upward sloping commodity prices. In general, we expect that there will be a positive correlation between farm profitability and the adoption of autonomous machines by farmers. This means increasing commodity prices and farm profits should foster the adoption of autonomous machines, while decreasing farm profitability would have the reverse effect.

2.2.4 Demographic and Social Change

The demands placed on agriculture to feed a growing population are well documented [59]. Population dynamics and social change will radically change demographics over the coming decades and out to and beyond 2045. Projected growth of the world's population is expected to be concentrated in Africa and South Asia and in urban environments. By mid-century, two-thirds of the global population will live in urban areas. Low-income countries will see large increases in the 15-24 years age group. The population will continue to grow in South Asia until at least 2045, and in sub-Saharan Africa until at least the end of the century. Cumulatively, these increments translate into a world population of 9.73 billion by 2050 and 11.2 billion by 2100. Significantly, by the year 2100, Asia and Africa are expected be home to a combined population of close to 82 % of the world's projected 11.2 billion population.

In these projections demographics out to 2045 are considered as a key driver of changes mainly for the inevitable demand for food and agricultural products but also in population dynamics, which includes diversity in regional trends, structure by age groups, and location, i.e., rural vs. urban. With regard to this analysis, something that will probably be more significant than population growth per se (which, roughly speaking, will lead to a 29 % increase in food demand), will be the increasing impact of urbanization. For decades, the world's population was predominantly rural. Even as late as the 1980's, more than 60 percent of the global population lived in rural areas. Since then, however, the urban-rural balance has changed dramatically and today it is estimated that only 45 % or so can be considered as rural. According to the United Nations, by 2050 this could be as low as 32 % [63]. Significantly, this predicted decline in rural population by 2050 is greater, by some 200 million, than the overall population increase; effectively leading to net decline in rural populations.

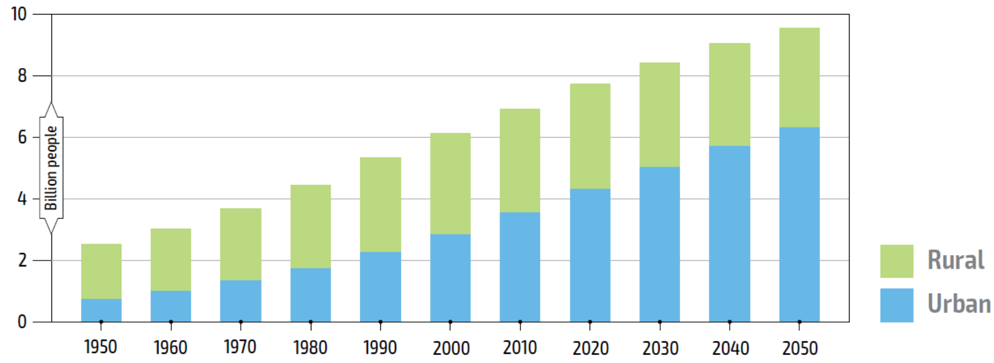

Figure 10 Predicted change in global urban vs. global rural populations out to 2050 [59].

Shrinking rural populations will further worsen the problem of agricultural labor supply that already exists in many countries and regions across the world. The declining attractiveness of being a farmer or working on a farm is expected to push the demand for labor-saving technologies such as autonomous machines. However, an increasing urbanization does not only foster the adoption of labor-saving technologies in agriculture but it also has an impact on food consumption patterns. Higher urban income tends to increase demand for processed foods, as well as animal-source food, fruits and vegetables, as part of a broad dietary transition [64] [65].

The final impact of demographics on the development of autonomous agricultural machinery is multi-dimensional, but most indicators show a need for continual uptake of rural labor-saving technologies.

2.2.5 Political and Economic Framework

The world economy grew by 2.6 % a year, almost doubling in size, between 1990 and 2014. During that period, global economic growth was driven mainly by low- and middle-income countries [59]. This trend of global growth being driven by emerging countries is expected to continue out to 2045, when, for example, the rise in global Gross Domestic Product (GDP) will outstrip that of the rise in OECD member countries.

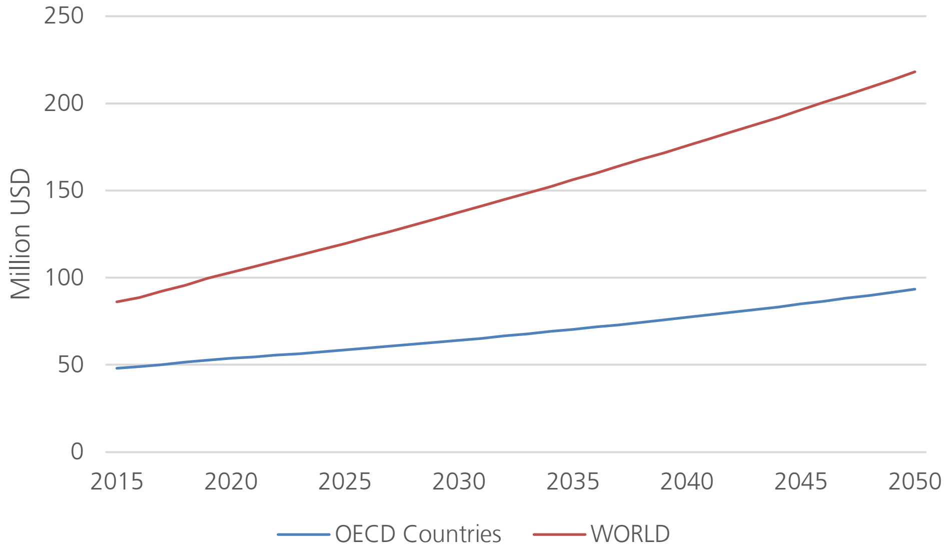

Figure 11 Real GDP long-term forecast (Global vs. OECD) 2015-2050 in million USD [62].

Furthermore, Price-Waterhouse-Coopers (PWC) predicts substantial and, from an agricultural point of view, important changes in the order of global economies [66]:

- The world economy could more than double in size by 2050 due to continued technology-driven productivity improvements
- Emerging markets (E7) could, on average, grow around twice as fast as advanced economies (G7)
- As a result, six of the seven largest economies in the world are projected to be emerging economies in 2050 – led by China (1st), India (2nd), and Indonesia (4th).
- The US could be down to third place in the global GDP rankings, while the EU27's share of world GDP could fall below 10 % by 2050.
- The UK could be down to 10th place by 2050, France out of the top 10, and Italy out of the top 20 as they are overtaken by faster growing emerging economies like Mexico, Turkey, and Vietnam, respectively.

The link between emerging markets, economic growth, and significantly higher demands for agricultural products is well documented. The economic growth of emerging markets in Asia, the Middle East, and Latin America leads to significant changes in diet [67]. People adopt a western lifestyle, which is associated with higher consumption of meat and dairy products. As a consequence, rising feed requirements put pressure on the agricultural markets, as do expanding biofuel requirements from arable crops. In effect, as the world grows richer, it grows hungrier.

The political framework, however, has the ability to offset this. One measure to meet increased demand for agricultural products are clearly global trade flows. Since 2000, trade in food products has grown strongly – more strongly than in the preceding decade at close to 8 % in real terms annually between 2001 and 2014 compared to just 2 % between 1990 and 2000. Apart from demand, one clear reason for the increased trade flows has been the global response to a more rules-based trading environment and, until recently, falling tariffs. Since 2017, however, increased protectionism policies in the US, China, Russia, and the EU as well as in other countries have reduced agricultural trade flows by imposing various layers of additional tariffs – the so-called "Trade Wars". While extremely damaging, such protectionism policies tend to be politically driven and on the whole are short-term (i.e., measured in years rather than decades) in nature.

The impact of any political and economic framework on the development of autonomous agricultural machinery should by all accounts be a positive one. Short-term political events will cause "bumps in the road", but the economy, which will be driven by what are essentially agricultural economies out to 2045, should be able to smooth out those negative influences.

2.2.6 Regulatory vs. Pest/Disease Pressure

Regulatory vs. pest/disease pressure is the final one of the most influential market-related factors impacting the market for autonomous agricultural machinery. As a driver, it is a mix of positive and negative elements and takes into account many of the "emerging disruptive technologies" which themselves are often driven by regulatory pressure or indeed unmet needs of the grower in relation to pest solutions.

It is well documented that most regulatory authorities around the world have a less than positive view on intensive agriculture and (at least publicly) have a more positive view on extensive and organic agriculture. Examples are the "Ecophyto Plan" in France or the "Zero Growth Policy" in China – both of which are designed to reduce the amount of pesticides used. The same reductions for the amount of fertilizers used is also a policy within the EU's 2018 legislative proposals to introduce a Farm Sustainability Tool for nutrients (including organic fertilizers) with the objective of improving water quality in Europe. Whether or not less intensive agriculture leads to a slower uptake of technology is a subject that is not well addressed in the literature. Less intensive agriculture implies a return to "organics" in a traditional sense, but at the same time opens up doors for "disruptive technologies" aided by precision farming and "Big Data" to reduce inputs and thereby achieve the regulators ultimate objective.

Regulatory pressure is not, however, universal across all nations. The EU's 2011 regulatory stance against GMO's (Genetic Modified Organisms) and its 2018 stance against Gene Edited Crops are in stark contrast to the United States' approval of such technologies. As a potentially disruptive technology, gene editing holds a lot of potential to dramatically reduce the requirements for virtually all inputs on arable and ultimately non-arable crops. To date, Asia and Africa are also firmly against the domestic cultivation of either GMO's or Gene Edited Crops although China's post 2020 stance on this will be pivotal.

One consequence of the increased regulatory pressure is that the growers "toolbox" for controlling weeds, pests, and diseases by chemical means is becoming smaller. While this is a greater problem in the EU (as indicated above), this pressure is felt across the globe. In some ways, new technologies (based on biologicals and/-or better conventional breeding) mitigate this downside, but on the whole the result is one of increasing pest and disease pressure. One direct impact seen in 2018 was the ban of neonicotinoid pesticides across the EU. This resulted in a significant change in the way growers control insect pests in certain crops from one requiring very low-volume controlled application of pesticides to one of much higher volume, less well-controlled application of pesticides – arguably with the need for greater machinery technology requirements. Additionally, the resurgence of pest problems included the development of Asian Rust in soybeans across Latin America and the development of severe infestations of Fall Army Worm across much of Africa and Asia in 2018 and 2019. Overall, it is felt that the intensity of pest problems, and in particular insect pests, will continue out to 2045.

The potential impact of regulatory and pest/disease pressure on the development of autonomous agricultural machinery is "less easy" to understand than many of the other drivers. In many ways, the move to less input and less intensive agriculture might slow down progress in some territories, while at the same time synergies between additional disruptive technologies and automation would have the reverse effect. Likewise, a predicted increase in pest pressure will likely lead to longer retention of "hard chemistry" (conventional pesticides) and a slow-down in the adoption of "soft chemistry", such as biologicals. "Hard chemistry" not only works better in conditions of high pest pressure but also, importantly for this study, requires more in the way of technologically advanced machinery.

2.3 Greatest Uncertainties

This section discusses the greatest challenges and contradictions in predictions of the future development of technology.

Pattern recognition (based on neural networks) seems to be on quite good path towards meeting the demands of assessing complex sensor data in real time. However, if the difference between objects (e.g., corn and weeds) is not significant, neural networks will have precision issues distinguishing crops from other objects [12] (e.g., "segmentation based on shape features is mostly effective in cases that little overlapping exists between the objects in the image" [12]). Scientists are still not sure how to tackle this problem. Many of the challenges, such as training of the neural networks and understanding why neural networks work so well, are still active fields of research.

New use cases call for **standardization** at the national and international level. Data security and data processing are major topics in technology research & development and in society as well. Experts point out that all the main data processing companies and providers are located in North America. The farmers outside of that region are concerned about the security of their data (see above). In general, there is a lack in the standards for safety and security regarding Big Data and finally for autonomous operations.

Experts claim that the major factor in adopting autonomy (i.e., the limiting factor) is the **legal situation**. The question arises: Will the legal situation provide a basis for complete autonomy? The experts answer the question (at least for Europe) with a clear "no" (at least for the near future). Furthermore, another question arising concerns how to get the machine to the field. In the era of autonomous operations, data is necessary for training. However, from the legal point of view, who "owns" the data from farms? Besides that, there is an overall issue with political instability in many areas, which is directly reflected in the acceptance of autonomy in some markets.

Agricultural operations are not repetitive and their environments are not characterized by well-defined and pre-determined tasks [19]. The **decision-making** process is complex. In order to replace humans, it will require proper input from an ever-increasing number of sensors and different types of sensors (besides purely visual ones). Otherwise, the process itself might introduce some difficulties. For example, picking crops too early is wasteful, but picking them too late slashes weeks off the storage time [4]. A lack of collaboration between research groups confounds this problem [1]. Very little field robot software has actually been released, published, and documented for others to use [1]. In this area communication between humans and machines as well as between machines is rather important to ensure digitalization of information from the field. However, there are only limited commercial products available for machine-to-machine communication, such as [19]. On the other hand, "it is not clear how telematics and infield communication solution platforms are open and how well multiple systems can interact" [19].

There are many **challenges** regarding **trust and acceptance** of autonomous operations. For example, in smaller agricultural areas, it is difficult to convince farmers that they need autonomous technology. Often, they do not want it (e.g., they consider it as luxury and as too fancy) and do not see the user benefit. Even more, they might see it as a threat to traditional agriculture and feel threatened by the challenges (e.g. loss of knowledge, lack of the ability to "feel" the field).

Process automation in agriculture exposes numerous **complex** autonomous **actions**. Without enough data, the machines will not learn properly. Therefore, platforms are required for data handling. Although some researchers claim that there is a great need for unified software platforms, some experts do not currently see a possibility for "control center solution" for the farmer to cover all required actions This rises a problem of the transmission of data over long distances (e.g., from the field). Second problem is that farmers do not use already existing solutions [2]. One of the reasons for this problem might be a misunderstanding between the industry and farmer needs. Not everything what the industry develops (e.g. special robots) is working for the farmers. New business models are required, especially in understanding the needs between universal and specific-dedicated machines (e.g., how an autonomous tractor will drive on the street?). On that track, experts offer their opinions regarding the drivers in the field. One of the experts, from our interviews, claims that in the near future, there are no indications that the driver will disappear from the machine. Contradictory opinion comes from another expert that claims that the technology will evolve to make the machines fully autonomous (around 2045). The farmer will act as a "controller" sitting at home or at the edge of the field. Machine might even become so independent to get the weather forecast and leave, for example, before rain is predicted to fertilize the field.

Sensor and actuator technologies are input/output interfaces of the autonomous operation process. The motivation for making actuation actions autonomous based on the input sensors is great: i) Currently modern agriculture uses a huge amount of energy in ploughing [11]; ii) the Food and Agriculture Organization of the United Nations estimates that 20–40 % of global crop yields are lost each year to pests and diseases, despite the application of around two-million tons of pesticides [4]. While autonomous use cases today employ a huge number of sensors, more is needed to achieve the same level of quality as with human assistance. Technology adaptation considers the addition of missing sensors, enabling the process in the field (e.g., connection of all the sensors), and proper actuators. Experts agree that some areas lack (data) infrastructure for communication, data transfer, etc. From the technology point of view, some sensors give out too many false warnings (e.g. UAV for field scouting and detection of crops and obstacles [3]) and there is a limit of how small things can be.

Summarizing the technological perspective, the current situation in the agricultural machinery market can be described as a market with a very high degree of automation (going back to 10-15 years ago). Automation does not only take place separately on individual machines but also across systems (entire processes and logistics). The mistakes made by humans can be well balanced by existing technology, and machines can already be operated optimally these days. Most experts and scientists agree that autonomy is inevitable and that we will witness the rise of autonomous operations in the next 25 years. However, there are also those who disagree with the idea of entirely automated farming systems. Basedvon their systematic survey about research and development in agricultural robotics, Shamshiri et al., claim: "It is not realistic to expect an entirely automated farming system in the future" [68]. Besides technology obstacles, there is heavy criticism regarding the social aspect, as some researchers claim that full autonomy would introduce some other challenges, such as the loss of farming knowledge [45]. From the state of the art, and based on our interviews with experts, it is easy to conclude that the scope of the challenges is huge and that even renowned scientists and experts face challenges in prioritizing and scoping all potential issues. In its functionality, technology enables autonomous operations even today already. However, existing quality aspects are the problem, and as these are developed and applied further, more and more new quality aspects emerge as challenges. Safety, security, and social aspects play the leading role. Existing solutions for pattern recognition and decision-making work with the desired functionality. However, they either do not provide the required quality of a functionality or do not quantify such quality at all.

From a market-related perspective, the factors that create the highest level of uncertainty are climate change and regulation. With respect to climate change, this uncertainty does not only mean that the development of the climate itself is unpredictable but also that its impact on agricultural production is hard to foresee. Either way, the impact may be manifold. First, in some regions arable land may become unusable if temperatures increase and droughts occur more often. Second, increasing volatility in terms of precipitation or natural disasters may lead to fluctuations in agricultural production, which would affect both farmers and consumers in terms of rising commodity prices for instance. These are just two potential direct impacts of climate change on agricultural production but there are indirect ones as well.

To slow down climate change and protect natural resources, governments can set up new rules and regulations under which farmers must produce. Such regulations and policies have a huge impact on the adoption of autonomous machinery by farmers. However, these regulations are usually implemented by politicians and ultimately driven by societies, who either support or neglect such changes. As one can currently observe in the US, elections have the potential to change this entirely and swing the needle from one direction to another. Even if these policies do not last forever and may be reverted, they can still distort the markets in the short-term. Therefore, regulation and policies seem to be subject to a high level of uncertainty as well.

2.4 Priority of Influencing Factors

One goal of the workshops performed with experts were to rank the aforementioned influencing factors based on their impact – either positive or negative – on the development of autonomous agricultural machinery. Every expert was asked to name three enablers/inhibitors that they believe to be the most important ones to watch out for. Afterwards, the individual indications were summarized and prioritized. According to the experts, the following enablers were identified as the most important ones (ranked according to relevance):

1. Available technology/technology adaptation (related to sensor and actuator technology, pattern recognition and decision-making process)
2. Achievement of increased productivity goals (related to farm productivity and profitability)
3. Trust and acceptance of autonomous technology by farmers
4. Machine-to-machine communication (related to complexity of autonomous actions)
5. Change of agricultural business models (related to consolidation in the AG industry and change of food production systems)
6. Change of climate and natural conditions
7. Limited resources (also related to climate change and natural conditions)
8. Regulatory vs. pest/disease pressure

All the experts concurred that "available technology/technology adaptation" is probably the most important influencing factor as this is the basis for development and automation will not happen if the technical implementation is not available. The second most important factor is "farm productivity/profitability". Against the background of an increasing global population, farmers are pushed to increase production – but without overusing natural resources. The experts believe that this is only possible if farmers increase their efficiency by adopting automated technologies. However, the "acceptance of farmers" is still unclear and might hinder this development. Some experts also think that in the future, multiple machines (maybe "robotic swarms") will operate on the field at the same time. To coordinate this work and enable simultaneous operations, reliable "machine-to-machine communication" is the key factor. Therefore, this is also a point of high relevance for the experts.

The top four enablers on the list, which were all mentioned multiple times by the experts, stand out a little bit in comparison to the last four points, which were only mentioned once or twice. Nevertheless, some experts also believe that "new agricultural business models" will emerge in the future that will change agricultural production systems and therefore also have an impact on the evolution of automation. This includes new production systems such as vertical farming (e.g. for fruit and vegetables) but also new business players such as Google or Microsoft, who might serve as data processors. The final three enablers on the list

– "climate change", "limited resources" and "regulation" – are somehow related to each other as one factor influences the other ones and vice versa. This means that "climate change" can lead to alternative "regulation" policies, which in turn affect the available "resources" that farmers can use. They all have in common that they directly determine the conditions under which farmers are able to produce.

3 System Classes of Agricultural Machinery and Development Scenarios for the Next 25 Years

In this section of the study, we want to sketch how experts in the field envision agricultural machinery with various levels of support and autonomy to develop within the next 25 years. For this purpose, we identify four levels of autonomy:

- **Entirely human-driven machines**, i.e., with no or low technological assistance
- **Assisted human-driven machines**, i.e., with technological assistance, e.g. with GPS assisted driving
- **Supervised autonomous machines**, i.e., using autonomous functions that are directly supervised by a human being.
- **Entirely autonomous machines**, i.e., without human supervision

In Section 3.1, we will describe how experts envision these system classes to develop within the next 25 years. In Section 3.2, we will describe these scenarios for different kinds of system classes for autonomous agricultural machinery.

3.1 Scenarios for Various Levels of Autonomy in the Next 25 Years

It is hard to envision within a time-frame of 25 years how technology will evolve. Therefore, we asked for opinions what the above-mentioned system classes would look like in the following stages: year 2025, year 2035, and year 2045. It was surprising, that the expert opinion was pretty homogeneous regarding the general development for these four stages. In the following, we will describe the expected development of the four system classes for each stage.

It is important to remember that the experts discussed these developments with a focus on tractor and combine development in mind, but the discussions were also extended to how smaller robots could affect the market.

Year 2025

Entirely human-driven machines: The experts estimate that entirely human driven machines will look very similar to entirely human-driven agricultural machinery today.

Assisted human-driven machines: The experts estimate that the machines will be equipped with more GPS-based navigation. Also, more machines will have camera systems. Machines are expected to provide site-specific recommendations. Furthermore, the experts expect that the amount of assistive technology for safety features will still be quite low.

Supervised autonomous machines: The experts estimate that there will still be a driver in the cabin. In contrast to later years, for 2025 the estimate is that one driver will be responsible for one machine in the majority of cases. In exceptional cases, maybe one driver will supervise two machines.

Entirely autonomous machines: The experts estimate that such machines will not be in the fields yet, but will be displayed in demo showcases or in closed units (buildings).

Year 2035

Entirely human-driven machines: The experts estimate that entirely human driven machines will look very similar to entirely human driven agricultural machinery today. So, there will be no great change compared to 2025.

Assisted human-driven machines: The experts estimate that the machines will be operated by a human driver and will be equipped with even more camera systems. Furthermore, they expect that the amount of assistive technology used for safety features will grow.

Supervised autonomous machines: The experts estimate that in the majority of cases supervised autonomous machines will be supervised by an expert operator, probably certified for this task, who will be online (wireless supervision) and no longer in the field. Some experts argue that the operator will still be near the machine to handle problems that may arise, so an operator may be driving one machine while supervising nearby machines. The autonomy of the machines will still be restricted to field- or application-specific tasks. The network infrastructure for machine-to-machine communication will be available.

Entirely autonomous machines: The experts estimate that entirely autonomous machines will be in the field with no driver in the cabin. They estimate that the machines will act autonomously once they are in the field. The machines will not drive to the field autonomously; rather a driver will drive the machine to the field (or, depending on size, they will be transported to the field in certain cases).

Year 2045

Entirely human-driven machines: The experts estimate that entirely human driven machines will still be around and will still look very similar to entirely human driven agricultural machinery today.

Assisted human-driven machines: The experts estimate that the machines will be operated by a human driver and will be similar to systems in 2035, but more reliable and well-tested.

Supervised autonomous machines: The experts estimate that the contact between the supervisor and the machines will decrease. Furthermore, they expect the supervised autonomous machines to have more universal applications (not only field- or application-specific autonomous functionality). The role of the supervisor will change from an operator to a system operator.

Entirely autonomous machines: The experts estimate that entirely autonomous machines and corresponding IT-systems will be able to decide everything, i.e., when to go out to the field or which crop protection to choose. The machines will be more universal, i.e., they will able to handle all implements. The operator will plan the tasks for the machines, e.g., in terms of scenarios. The farm management systems will probably execute the intelligence to distribute the tasks to the machines. Some experts also argue that the machines will be able to drive out to the field by themselves without an operator. If so, a garage next to the field would avoid accidents or regulatory restrictions.

3.2 Autonomous Machinery in Agricultural Work Processes

The general work steps of an agricultural year are shown in Figure 12. Today, the farmer is the central executive organ of these work steps. Additionally, logistics plays a central role in the execution of the individual work steps in terms of refilling the machines, or transport between fields. It is important to keep in mind that various crops have different cultivation requirements and that a farmer's crop rotation is defined by agricultural, environmental and economic factors. The automation potentials of the single work steps will be described below.

Tillage is used for the crushing, splitting and mixing of harvest remains. In addition, weed seeds and lost crop seeds are stimulated to germinate and afterwards destroyed in a second tillage pass. Additionally, the evaporation of water is reduced [69]. Many different implements for tillage are available, and efficient machine control systems are implemented (or in development) to reduce parameters such as fuel consumption. In addition to these improvements, the focus is shifting to automatic recording of the work results. For example, camera systems can be used to determine the condition of the ground cover (soil surface covered with plant residues) [70]. Another example: Using electromagnetic induction, it is possible to record soil parameters (e.g., soil compaction, soil type). The data can be used in real time for various kinds of implement control (depth control in terms of tillage). Besides, it is possible to use this information to support the creation of application maps [71] [72]. Tillage has high energy requirements in terms of tractive power. For this reason, it is likely that in the future, existing tractor systems will be automated rather small robots being used [68].

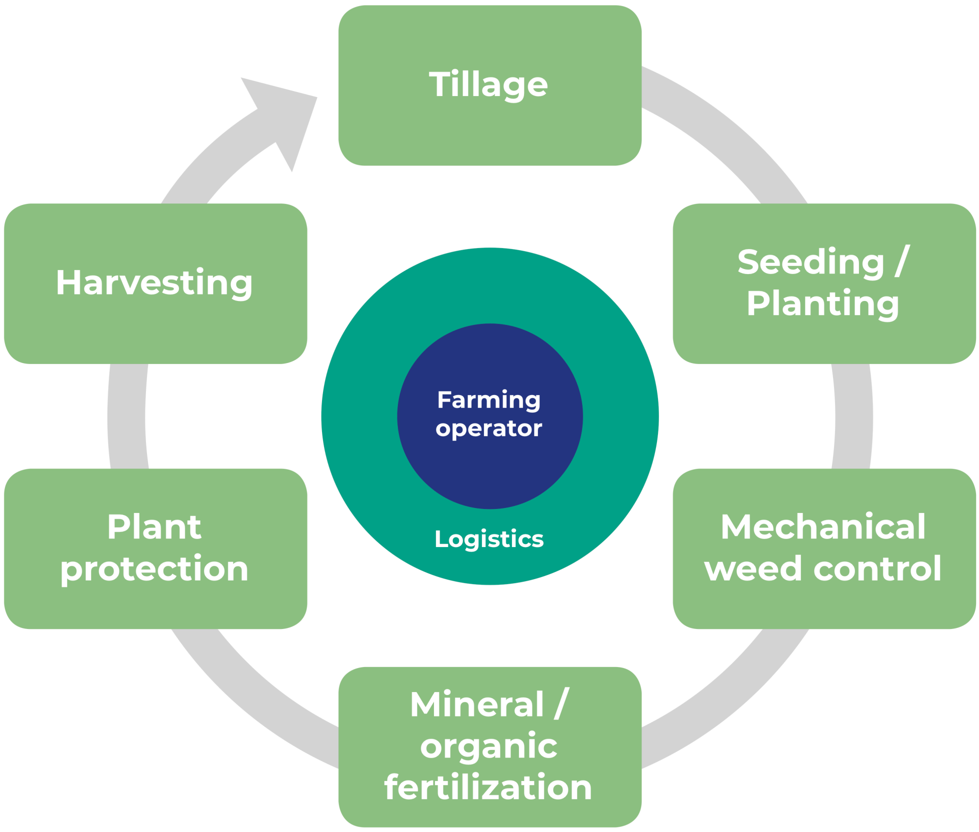

Figure 12 Main work steps of the farm operator during a plant production cycle (own illustration).

Seeding: It is important to have an appropriate seed bed and seed placement [69]. Appropriate seeding depth is important for optimum germination and plant development. There are technical approaches for continuously monitoring the placement depth of seed, and technical monitoring in real time is already possible [73] [74]. In this area, the focus is on variable seed application, precision seeding with the help of simulation models and real time monitoring [75]. For the work step "Seeding" lower tractive power is required and hence, it is also possible to use small robotic systems. Depending on the robot size, robot units must act in swarms to achieve area performance that is comparable to existing systems [76] [77]. Swarm systems with larger autonomous vehicles are also possible depending on the size of the farm [70]. From a technical point of view, the basic conditions for an autonomous process have been met and the scenarios presented are therefore conceivable in the future.

Mechanical weed control: Weed control before row closure can be either mechanical or chemical. Mechanical weed control is becoming more and more important due to prohibitions of individual active substances and resistance problems of individual pesticides. In the field of mechanical weed control, in particular for root crops like sugar beets and maize (high row distance), robotics technology is well advanced. For example, robots are able to eliminate weeds in the rows [78]. The agricultural machinery industry has set the focus on hoeing, and it is already possible to hoe between and within rows based on GPS-coordinates and camera systems [79]. Mechanical weed control was one of the first fields of automation in agriculture [80]. Hence, the autonomy potential is high.

Mineral or organic fertilization: Fertilization is carried out to an optimal special intensity, which takes into account economic, agronomic and environmental aspects. In mineral fertilization, the focus is on technologies that optimize distribution quality and thus distribution accuracy. The technology for sensor-based and satellite-based variable rate applications is improving continuously and promises to be increasingly accepted [81]. All in all, an autonomous design is technically feasible, but the area performance of todays' systems must be taken into account. For this reason, it is difficult to estimate robotic size. In contrast to mineral fertilizers, manure has a very heterogeneous nutrient composition. With the help of NIR sensors, the nutrients in the manure can be determined in real time and applied as required. The application of manure can be carried out autonomously, but the challenges are logistics (manure to field), soil compaction and area performance. Manure application with hose systems may be an alternative. Previous systems will probably be automated or new process approaches will be used.

Crop protection: The application of pesticides is similar to the application of mineral fertilizer. Manufacturers are improving the sprayers to enable accurate and precise applications. Some companies rely on technologies that detect weeds and plant diseases to specifically apply pesticides (see & spray) [82]. The technical knowledge for carrying out spraying autonomously is available in principle. In practical implementation, area performance must be taken into account.

Harvesting: The harvest is performed by the combine harvester or by self-propelled harvesting machines. The tasks of a combine are subdivided as follows: cutting and picking, threshing and separation, cleaning and collecting, chopping and distributing straw. The threshing and separation processes are difficult to detect by sensors. However, it is possible to record the result at the end, such as grain loss, straw in the grain and percentage of broken grain [80]. The driver's work is facilitated by the increasing intelligence of the machines. A combine automatically adjusts its machine settings to the specified guide values in real time at optimum speed. NIR sensors can be used to detect the ingredients of the grain. In Japan, autonomous combines have been tested in practice [83]. Another idea is to split the harvesting process into single steps. Logistics and transport of harvested goods will remain a challenge.

In these days, in highly industrialized countries people tend not to work on farms anymore. Therefore, the technical development in terms of autonomous systems like robots will be pushed even more. According to experts, robot size is crucial in terms of area performance.

Small units of robotic swarms are interesting because of their low weight, which results in negligible soil compaction. However, according to some experts, they will still remain a niche solution for single agriculture process steps.

Due to technological development, a rethinking and restructuring of established processes is also conceivable and possibly beneficial in terms of integrating and establishing autonomous systems in practice. Regarding to experts, hybrid systems are a permanent or maybe even a transition solution. Depending on the technical requirements, individual work steps will be carried out autonomously and other tasks assisted by a driver. In this context, modular cabin concepts make sense in order to reduce costs of expensive cabins. Regarding to experts, autonomous systems will be modular in the future and will replace classic tractor and implement systems.

In summary, the focus of technical development is on site-specific farming (independent of machine size) to make single work processes more efficient.

4 Market Assessment

As already indicated above, the main focus of this study is on identifying and describing the main influencing factors that drive the autonomous agricultural machinery market – from a qualitative perspective. This section, however, is designed to give readers also an idea about the potential quantitative market development within the next 25 years.

In general, a quantitative market forecast is indeed a challenging exercise as:

- Many state-of-the-art technologies are still being developed and their application to agricultural production has to be proven. Hence, except for some prototypes autonomous machines have not been used commercially by farmers yet.
- The current farm structure and degree of mechanization differs strongly between some regions and countries, so the rate at which farmers are adopting autonomous machines – once they are commercially available – is expected to vary considerably, too.
- The forecast horizon until 2045 is rather long. For this time period, there exist only few long-term projections for agricultural markets and the related influencing factors – which in turn also include a lot of uncertainty.

The lack of historical data on autonomous machines and reliable projections about the influencing factors going forward make a solid quantification of the different classes of autonomous agricultural machines difficult. To overcome this problem, we used the following approach:

1. First, we focused on tractor sales only and used annual sales data as well as FAO projections [52] for market-related influencing factors to estimate the total tractor demand in different regions for the years 2025, 2035, and 2045 (see section 4.1). With regard to the available sales data, we cannot distinguish between different size classes (e.g. in terms of horsepower) or automation categories here but merely calculated a baseline for total market driven tractor demand.
2. Second, to map the technological development to the total tractor demand, we asked the experts what they believe the relative market share of the four considered automation classes (i.e. entirely human driven, assisted human driven, supervised autonomous, and entirely autonomous) will be in 2025, 2035, and 2045 (section 4.2). By applying the experts' estimates to the calculated baseline, we can split the total tractor demand into the different automation classes and derive an estimate for each type of automation. Readers

should keep in mind, however, that due to the challenges and difficulties mentioned above, the figures can only serve as a rough guideline for the expected market development.

4.1 Rough Forecast of Market Development

In this subsection, we want to show how the total global and regional demand for tractors might develop out to the year 2045. This means we really look at the development of annual tractor sales and not at the total fleet of tractors that are used for agricultural production in certain countries or regions. To some extent, these variables are correlated with each other, of course, but our quantitative analysis is based on historical data about annual tractor sales collected from various sources for selected countries.

Depending on regional farm characteristics (e.g., number and average size of farms), the types and numbers of tractors sold per year can differ substantially. Measured in absolute terms, most of the tractors worldwide are sold in the Asian countries China and India – although these tractors are on average much smaller and less technologically advanced than those sold in North America or Western Europe. Unfortunately, the publicly available data on tractor sales is not so comprehensive that it allows us to account for such features and differentiate by horsepower classes. Instead, we can only work with total tractor sales here, which is our target variable.

The set of market-related explanatory variables that have an impact on tractor sales and that we use to predict the future market development is largely based on FAO data. The reason why we use FAO data for this is that FAO provides both historical and forward-looking data (projections until 2050) for a consistent set of variables such as harvested area, gross value of agricultural production, rural/urban population, number of livestock etc. Hence, we can first use the historical data in a regression framework and estimate a functional relationship between those explanatory variables and tractor sales. Afterwards, we use the projected development of those explanatory variables to calculate future tractor sales.

Within their agricultural projections, the FAO provides three different scenarios based on different political, social, or economic assumptions. For this analysis, we decided to use the scenario called "towards sustainability" as we believe that societies demand this and a continuation of "business as usual", which would be another scenario, is not very likely in the long run. As these scenarios turn out to be rather different though, choosing one or the other would certainly change the outcome of this analysis.

The development of tractor sales for the years 2025, 2035, and 2045, which we derived from our analysis is presented in Table 1. To account for different market characteristics and speed of technological adoption by farmers, we decided to group similar countries together and defined the following clusters:

- High-technology, large-scale markets (USA, Canada, Australia)
- Low-technology, large-scale markets (Brazil, Argentina, Mexico)
- Western European markets (France, Germany, Italy, Spain, UK)
- Eastern European markets (Russia, Poland)
- Small-scale Asian markets (China, India, Japan, Korea)
- African & Middle Eastern markets (South Africa, Turkey)

This definition is driven by technological and structural aspects and does not necessarily correspond with geographic regions. The countries mentioned in parentheses are those where historical tractor sales data was available and that we used in our calculations. Although this is a relatively small sample size, the countries represent a large share of the global market accounting for approximately 80 % of global tractor sales. The estimated future development of tractor demand in the different markets is presented in Table 1. The arrows are supposed to indicate whether the total tractor sales increase, decrease, or stay the same compared to the previous point in time.

On a global basis, we can conclude that the demand for tractors is expected to increase both in 2025 and 2035, but stays the same afterwards. This is mainly driven by the Asian markets, which continue to grow as a whole. A similar picture can be observed in the high-technology large scale North American market, which is also expected to grow until 2035 but start to decrease afterwards. Such a decrease of demand will set in even earlier in the Western and Eastern European market, which is expected to slightly improve until 2025 though. Somewhat surprisingly, the tractor demand in both the low-technology large-scale market and the African market is projected to continuously shrink over time.

It is important to keep in mind that these tendencies just relate to the total number of tractors (in units) that are expected to be sold on average in the respective year. We can neither make a statement on the types nor on the value of the tractors being sold. This means that even if a market is expected to decline in terms of total unit sales, there might still be an upward sloping trend in certain tractor categories: i.e., sales of larger (in terms of horsepower) or more technologically advanced machines might still increase.

Table 1 Development of annual tractor sales (in units), own estimation on the basis of historical tractor sales data for the selected countries mentioned above and FAO's agricultural long-term projections until 2050.

Development of annual tractor unit sales	Estimated share of global sales (2009-2018)	2025 vs. 10-year average 2009-18	2035 vs. 2025	2045 vs. 2035
High-technology large-scale markets (North America & Australia)	15 %	↑	↑	↓
Western European markets	7 %	→	↓	↓
Small-scale Asian markets	67 %	↑	↑	↑
Low-technology, large-scale markets (Latin America)	4 %	↓	↓	↓
Eastern European markets	3 %	↑	↓	↓
African & Middle Eastern markets	4 %	↓	↓	↓
Total global market	100 %	↑	↑	→

4.2 Assessment According to System Type

In this section, we will illustrate how the different types of automation will be distributed in the selected markets in 2025, 2035, and 2045. The results presented in the tables below are entirely based on the assessment of experts. The size of the circles represents the relative market share of the respective automation type. We use the classification shown in Table 2.

Table 2 Legend for the tables in this section.

Legend				
Market share	> 80 %	50 – 80 %	10 – 50 %	< 10 %

For the year 2025 (cf. Table 3), the experts agreed that in most markets the situation will be more or less comparable to the current status quo. This means that there no entirely autonomous machines will be used commercially by farmers. Moreover, even the class of supervised autonomous machines will just represent a niche market in the high-technology regions of North America and Western Europe. Except for the African and maybe the small-scale Asian market, assisted human-driven tractors and combines will account for the biggest market share in all regions. The African markets will still be dominated by machines without technological assistance in 2025, and the experts assume that this will still be the case in 2035 (cf. Table 4).

Table 3 Market share of automation type for the year 2025, estimation based on expert interviews/workshops.

Year 2025	Entirely human-driven (no technological assistance)	Assisted human-driven (with technological assistance, e.g., GPS)	Supervised autonomous machines	Entirely autonomous machines
High-technology, large-scale markets (North America & Australia)				---
Western European markets				---
Small-scale Asian markets				---
Low-technology, large-scale markets (Latin America)			---	---
Eastern European markets			---	---
African & Middle Eastern markets			---	---

Table 4 Market share of automation type for the year 2035, estimation based on expert interviews/workshops.

Year 2035	Entirely human driven (no technological assistance)	Assisted human driven (with technological assistance, e.g., GPS)	Supervised autonomous machines	Entirely autonomous machines
High-technology, large-scale markets (North America & Australia)				
Western European markets				
Small-scale Asian markets				
Low-technology, large-scale markets (Latin America)				---
Eastern European markets				---
African & Middle Eastern markets				---

In contrast to this, the North American, Australian, Western European and Asian markets will probably already see the first entirely autonomous machines operating in the fields. Although the market share of entirely autonomous machines in the large-scale North American markets is estimated to be higher than in Western Europe, some experts believe that the shift towards automation will begin in Western Europe, as the pressure for farmers to be more sustainable is much higher here than in other regions. The American and Asian markets will follow. Interestingly, the experts also believe that farmers in Asia will be more tempted to skip the stage of supervised autonomy and invest directly into entirely autonomous machines. Nevertheless, the classical human-driven machines – regardless of technological assistance – will remain the largest class in all regions in 2035.

By the year 2045 (cf. Table 5), this will have changed, however, in the high-technology, large-scale North American and Western European markets. According to the experts, the majority of agricultural machines in these markets will operate either in supervised mode or entirely autonomously, whereas human-driven tractors and combines will only have a marginal market share. The experts were not sure whether the higher share of autonomous agricultural machines will be in North America or in Western Europe. They came to the conclusion that this will largely depend on laws and legislation in those regions – which will either enable or inhibit the operation of autonomous machines. In terms of automation, the other regions are still expected to lag behind. Although the Latin American and Eastern European markets will also develop in this direction, human-driven machines are still expected to represent a significant market share.

Table 5 Market share of automation type for the year 2045, estimation based on expert interviews/workshops.

Year 2045	Entirely human driven (no technological assistance)	Assisted human driven (with technological assistance, e.g. GPS)	Supervised autonomous machines	Entirely autonomous machines
High-technology, large-scale markets (North America & Australia)				
Western European markets				
Small-scale Asian markets				
Low-technology, large-scale markets (Latin America)				
Eastern European market				
African & Middle Eastern Markets				

4.3 Greatest Uncertainties

When looking at the total tractor market development in section 4.1, or the distribution of automation classes in section 4.2, one should not forget that both forecasts are still subject to a high level of uncertainty. In fact, the level of confidence decreases with the length of the forecast horizon as key influencing factors might develop completely differently than anticipated today.

Our estimations of the total tractor demand are based on FAO projections, for instance, which in turn are based on certain assumptions on policies, economic development or natural conditions. These may very well change in the course of time and thus may lead to higher/lower tractor demand in the end. Particularly policy and regulation decisions, which are often driven by societal changes and can foster or slow down structural changes in agricultural production, are hard to predict. It is also noteworthy that the figures that we calculated in section 4.1, only refer to the average number of tractors expected to be sold annually. This does exclude short-run fluctuations, which may occur and result in higher/lower sales in a particular year.

What is also important to mention is that we only had information on a limited set of variables for our estimations, and could not account for some potentially relevant influencing factors, such as tractor prices for instance, where no complete dataset was available. The development of future machinery prices is hard to foresee and also a major source of uncertainty. The prices will certainly affect the total demand for agricultural machines, but may even have a greater impact on the proportion of the different automation classes. If the prices for supervised and entirely autonomous machines are significantly higher than those for human-driven machines, this might eradicate any operational efficiency gains and hamper farmers´ willingness to invest in autonomy.

Further progress in research on biotechnology or gene editing may also be a game changer in the future, which has the potential to reshape huge parts of agricultural production. In countries and regions, where societies accept these technologies, agriculture might develop in a different direction than in those countries where such technologies are not approved. In the end, this will also affect the adoption of autonomous machinery by farmers and potentially intensify differences across regions.

The increasing level of uncertainty out to the year 2045 also became also visible in the discussions with the experts. While they were pretty confident estimating the market shares in 2025 based on their knowledge and personal experience, they were really challenged when they were asked about their evaluation of the different markets in 2045 and could only specify a broader range of possible market shares.

5 Summary and Conclusion

This study had the aim to scout the state of art as well as the future development of the autonomous agricultural machinery market. First, the relevant factors that will influence the development of autonomous machinery in the market were identified including estimating their importance, understanding the biggest uncertainties and getting a feeling how the state of the practice and art as well as the experts see future developments. From our perspective 13 influence factors, categorized into technology-related and market-related factors, will play a decisive role. On this basis, experts in the field prioritized four factors as most important influence factors: (1) available technology/technology adaptation, (2) the achievement of increased productivity goals, (3) trust and acceptance of autonomous technology by farmers and (4) machine-to-machine communication. In addition, many uncertainties with regard to the influence factors were taken into account as well, e.g., with regard to the factors climate change and policies/regulations, which also have a counter-effect on other factors (e.g., farm productivity/profitability) and have the potential to reshape agricultural production systems.

Key Development for the four classes of entirely human-driven, assisted human-driven, supervised autonomous and entirely autonomous systems were discussed with a preview how these systems will look like in the years 2025, 2035 and 2045. Whereas the entirely human-driven systems will remain similar to today's shape, significant changes are expected to the other three classes. Assisted systems will be able to support more complex actions, being equipped with more cameras and more safety features. The class of supervised autonomous machines will evolve with lower demands on supervisor presence and qualification over time and an increase from field- and application specific autonomous actions towards more universal actions. The class of entirely autonomous machines develops from pure demo systems via systems that act autonomously on the field with defined plans once they are there towards systems that receive rough planning via other systems and then act completely autonomously.

Finally, a quantitative estimate of the future market development is given which is calculated on the total tractor demand (based on available data on tractor sales and FAO projections) on the one hand, and the adoption rate of different automation classes (by asking experts) on the other hand. While total tractor demand is mainly driven by Asian countries, the experts believe that the uptake of autonomous technology will be led by North America and Western Europe.

In general, we can conclude that there will be a clear move towards autonomous agricultural systems in the long-run but the speed at which farmers adopt autonomous systems will differ substantially between different regions/markets. This is also a result of the different farm and production structures, of course.

References

[1] Jensen K, Larsen M, Nielsen S, Larsen L, Olsen K, Jørgensen R. Towards an Open Software Platform for Field Robots in Precision Agriculture. Robotics 2014;3(2):207–34.

[2] Hunt ER, Daughtry CST. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? International Journal of Remote Sensing 2017;39(15-16):5345–76.

[3] Walter A, Khanna R, Lottes P, Stachniss C, Siegwart R, Nieto J et al. Flourish -A robotic approach for automation in crop management. International Conference on Precision Agriculture 2018:1–9.

[4] King A. Technology: The Future of Agriculture. Nature 2017;544(7651):S21-S23.

[5] Antille DL, Lobsey CR, McCarthy CL, Thomasson JA, Baillie CP. A review of the state of the art in agricultural automation. Part IV: Sensor-based nitrogen management technologies. In: 2018 American Society of Agricultural and Biological Engineers, Annual International Meeting, At Detroit, Michigan.

[6] VDI Technologiezentrum GmbH. HYLAP: Hyperspektrale Prozesskontrolle in der Lebensmittel- und Agrarproduktion der Zukunft 4.0. [October 28, 2019]; Available from: https://www.photonik-forschung.de/projekte/photonische-prozessketten/projekt/hylap.html.

[7] Wang S, Song J, Lien J, Poupyrev I, Hilliges O. Interacting with Soli: Exploring Fine-Grained Dynamic Gesture Recognition in the Radio-Frequency Spectrum. In: Annual Symposium on User Interface Software and Technology, Tokyo, Japan, 2016., p. 851–860.

[8] Parzer P, Bauer S, Haller M, Perteneder F, Probst K, Rendl C et al. RESi: A Highly Flexible, Pressure-Sensitive, Imperceptible Textile Interface Based on Resistive Yarns. In: ACM Symposium on User Interface Software and Technology 2018, p. 745–756.

[9] Withana A, Groeger D, Steimle J. Tacttoo: A Thin and Feel-Through Tattoo for On-Skin Tactile Output. In: Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology, 2018, p. 365–378.

[10] Kim LH, Follmer S. SwarmHaptics. In: Brewster S, Fitzpatrick G, Cox A, Kostakos V, editors. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems - CHI '19. New York, New York, USA: ACM Press; 2019, p. 1–13.

[11] Harrington K, Large D, Burnett G, Georgiou O. Exploring the Use of Mid-Air Ultrasonic Feedback to Enhance Automotive User Interfaces. Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Toronto, Canada 2018:11–20.

[12] Duckett T, Pearson S, Blackmore S, Grieve B. Agricultural Robotics: The Future of Robotic Agriculture; Available from: https://arxiv.org/ftp/arxiv/papers/1806/1806.06762.pdf.

[13] Kiani S, Jafari A. Crop detection and positioning in the field using discriminant analysis and neural networks based on shape features. Journal of Agricultural Science and Technology 2012;14(4):755–65.

[14] Pérez AJ, López F, Benlloch JV, Christensen S. Colour and shape analysis techniques for weed detection in cereal fields. Computers and Electronics in Agriculture 2000;25(3):197–212.

[15] Cho S, Jeong J, Lee D. Weed-plant discrimination by machine vision and artificial neural network. Biosystems Engineering 2002;83(3):275–80.

[16] Åstrand BS, Baerveldt A-J. A mobile robot for mechanical weed control. International Sugar Journal 2003;105(1250):89–95.

[17] Castaño F, Beruvides G, Haber RE, Artuñedo A. Obstacle Recognition Based on Machine Learning for On-Chip LiDAR Sensors in a Cyber-Physical System. Sensors (Basel, Switzerland) 2017;17(9).

[18] Farias G, Fabregas E, Peralta E, Vargas H, Hermosilla G, Garcia G et al. A Neural Network Approach for Building An Obstacle Detection Model by Fusion of Proximity Sensors Data. Sensors (Basel, Switzerland) 2018;18(3).

[19] Bauckhage C, Kersting K. Data Mining and Pattern Recognition in Agriculture. Künstliche Intelligenz (KI - Künstliche Intelligenz) 2013;27(4):313–24.

[20] Baillie CP, Thomasson JA, Lobsey CR, McCarthy CL, Antille DL. A review of the state of the art in agricultural automation. Part I: Sensing technologies for optimization of machine operation and farm inputs. American Society of Agricultural and Biological Engineers, Annual International Meeting 2018.

[21] Baillie CP, Thomasson JA, Lobsey CR, McCarthy CL, Antille DL. A review of the state of the art in agricultural automation. Part III: Agricultural machinery navigation systems. American Society of Agricultural and Biological Engineers, Annual International Meeting 2018.

[22] Bechar A, Vigneault C. Agricultural robots for field operations: Concepts and components. Biosystems Engineering 2016;149:94–111.

[23] Montemerlo M, Roy N, Thrun S. Perspectives on standardization in mobile robot programming the Carnegie Mellon Navigation (CARMEN) Toolkit. In: Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453): IEEE; 2003, p. 2436–2441.

[24] Nesnas IAD, Wright A, Bajracharya M, Simmons R, Estlin T. CLARAty and challenges of developing interoperable robotic software. In: Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453): IEEE; 2003, p. 2428–2435.

[25] Cepeda JS, Chaimowicz L, Soto R. Exploring Microsoft Robotics Studio as a Mechanism for Service-Oriented Robotics. In Proceedings of the Robotics Symposium and Intelligent Robotic Meeting (LARS), Latin American, Sao Bernardo do Campo, Brazil 2010:7–12.

[26] Quigley M, Gerkey B, Conley K, Faust J, Foote T, Leibs J et al. ROS: An open-source Robot Operating System. Proceedings of the ICRA Workshop on Open Source Software, Kobe, Japan 2009.

[27] Makarenko A, Brooks A, Kaupp T. Orca: Components for Robotics. Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems 2006.

[28] Bruyninckx H. Open robot control software: the OROCOS project. In: 2001 IEEE international conference on robotics and automation: IEEE; 2001, p. 2523–2528.

[29] García-Pérez L, García-Alegre MC, Ribeiro A, Guinea D. An agent of behaviour architecture for unmanned control of a farming vehicle. Computers and Electronics in Agriculture 2008;60(1):39–48.

[30] Beck AB, Andersen NA, Andersen JC, Ravn O. MobotWare – A Plug-in Based Framework for Mobile Robots. IFAC Proceedings Volumes 2010;43(16):127–32.

[31] Thomasson JA, Baillie CP, Antille DL, McCarthy CL, Lobsey CR. A review of the state of the art in agricultural automation. Part II: On-farm agricultural communications and connectivity. American Society of Agricultural and Biological Engineers, Annual International Meeting, At Detroit, Michigan, 2018.

[32] Bechar A, Vigneault C. Agricultural robots for field operations. Part 2: Operations and systems. Biosystems Engineering 2017;153:110–28.

[33] Schimmelpfennig D. Farm Profits and Adoption of Precision Agriculture. [October 24, 2019]; Available from: https://www.ers.usda.gov/webdocs/publications/80326/err-217.pdf?v=0.

[34] Milioto A, Lottes P, Stachniss C. Real-time Semantic Segmentation of Crop and Weed for Precision Agriculture Robots Leveraging Background Knowledge in CNNs; 2017.

[35] McCool CS, Beattie J, Firn J, Lehnert C, Kulk J, Bawden O et al. Efficacy of Mechanical Weeding Tools: a study into alternative weed management strategies enabled by robotics. IEEE Robot. Autom. Lett. 2018:1.

[36] Riggio G, Fantuzzi C, Secchi C. A Low-Cost Navigation Strategy for Yield Estimation in Vineyards. IEEE International Conference on Robotics and Automation (ICRA) 2018:2200–5.

[37] Thayer TC, Vougioukas S, Goldberg K, Carpin S. Routing Algorithms for Robot Assisted Precision Irrigation. In: Lynch K, Automation IICoRa, editors. 2018 IEEE International Conference on Robotics and Automation (ICRA): 21-25 May 2018. [Piscataway, NJ]: IEEE; 2018, p. 2221–2228.

[38] Mutschler AS. Towards Autonomous Farming. [October 22, 2019]; Available from: https://semiengineering.com/toward-autonomous-farming/.

[39] SAE International. Automated Driving - Levels of Driving Automation are Defined in New SAE International Standard J3016 2014.

[40] Koopman P. An Overview of Draft UL 4600: Standard for Safety for the Evaluation of Autonomous Products. [October 22, 2019]; Available from: https://medium.com/@pr_97195/an-overview-of-draft-ul-4600-standard-for-safety-for-the-evaluation-of-autonomous-products-a50083762591.

[41] ISO-Standard. ISO/PAS 21448:2019 Road vehicles — Safety of the intended functionality. [October 21, 2019]; Available from: https://www.iso.org/standard/70939.html.

[42] N.N. Homologation. [October 24, 2018]; Available from: https://searchcio.techtarget.com/definition/homologation.

[43] Bostrom N, Yudkowsky E. The ethics of artificial intelligence. In: Frankish K, Ramsey WM, editors. The Cambridge handbook of artificial intelligence. Cambridge: Cambridge University Press; 2014, p. 316–334.

[44] Ong Y-S, Gupta A. AIR5: Five Pillars of Artificial Intelligence Research. IEEE Transactions on Emerging Topics in Computational Intelligence 2019;3(5):411–5.

[45] Dawoud M, Altilar DT. Cloud-based E-health systems: Security and privacy challenges and solutions. In: 2nd International Conference on Computer Science and Engineering: Antalya-Türkiye 5-8 Ekim (October) 2017. New York: IEEE; 2017, p. 861–865.

[46] Bertino E. Big Data - Security and Privacy. In: Carminati B, editor. 2015 IEEE International Congress on Big Data (BigData Congress): June 27, 2015 - July 2, 2015, New York, New York, USA. Piscataway, NJ: IEEE; 2015, p. 757–761.

[47] Devitt SK. Cognitive factors that affect the adoption of autonomous agriculture. Farm Policy Journal 2018;15(2):49–60.

[48] Archer DW, Dawson J, Kreuter UP, Hendrickson M, Halloran JM. Social and political influences on agricultural systems. Renewable Agriculture and Food Systems 2008;23(04):272–84.

[49] The Telegraph. Top 10 technologies that were ahead of their time. [October 15, 2019]; Available from: https://www.telegraph.co.uk/technology/news/11377731/Top-10-technologies-that-were-ahead-of-their-time.html.

[50] Collins M, Knutti R, Arblaster J, Dufresne J-L, Fichefet T, Friedlingstein P et al. Long-term Climate Change: Projections, Commitments and Irreversibility. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change 2013:1029–136.

[51] Nearing MA, Pruski FF, O'Neal MR. Expected Climate Change Impacts on Soil Erosion Rates: A Review. Journal of Soil and Water Conservation 2004;59(1):43–50.

[52] FAO. The Future of food and agriculture - Alternative Pathways to 2050. Summary version. [October 14, 2019]; Available from: http://www.fao.org/3/CA1553EN/ca1553en.pdf.

[53] Tubiello FN, Salvatore M, Cóndor Golec RD, Ferrara A, Rossi S, Biancalani R et al. Agriculture, forestry and other land use emissions by sources and removals by sinks. Statistics Division, Food and Agriculture Organization: Rome 2014.

[54] European Commission. Farm Structures. [October 15, 2019]; Available from: https://ec.europa.eu/info/sites/info/files/food-farming-fisheries/farming/documents/farm-structures_en.pdf.

[55] USDA, National Agricultural Statistics Service. Farms and Land in Farms 2018 Summary 04/18/2019. [October 12, 2019]; Available from: https://www.nass.usda.gov/Publications/Todays_Reports/reports/fnlo0419.pdf.

[56] Sheng Y, Ding J, Huang J. The Relationship between Farm Size and Productivity in Agriculture: Evidence from Maize Production in Northern China. American Journal of Agricultural Economics 2019;101(3):790–806.

[57] FAO. 2000 world census of agriculture: Analysis and international comparison of the results (1996-2005). Rome: Food and Agriculture Organization of the United Nations; 2013.

[58] European Commission. Farm structure survey 2016. [October 23, 2019]; Available from: https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=ef_m_farmleg&lang=en.

[59] FAO. The future of food and agriculture: Trends and challenges. Rome: Food and Agriculture Organization of the United Nations; 2017.

[60] Key ND, Roberts MJ. Commodity Payments, Farm Business Survival, and Farm Size Growth. United States. Dept. of Agriculture. Economic Research Service; 2007.

[61] Bellmann C, Hepburn J. The Decline of Commodity Prices and Global Agricultural Trade Negotiations: A Game Changer? poldev 2017;8(1).

[62] OECD/FAO. OECD-FAO Agricultural Outlook 2018-2027. Rome: OECD Publishing; 2018.

[63] United Nations, Department of Economic and Social Affairs, Population Division. World Urbanization Prospects: The 2018 Revision(ST/ESA/SER.A/420). New York: United Nations; 2019.

[64] Wang Y-s. The Challenges and Strategies of Food Security under Rapid Urbanization in China. Sustainability 2019;11(2):542.

[65] Regmi A, Dyck J. Effects of Urbanization on Global Food Demand. [October 16, 2019]; Available from: https://www.ers.usda.gov/webdocs/publications/40303/14974_wrs011e_1_.pdf?v=0.

[66] Hawksworth J, Audino H, Clarry R. The Long View - How will the global economic order change by2050? [October 12, 2019]; Available from: https://www.pwc.com/gx/en/world-2050/assets/pwc-the-world-in-2050-full-report-feb-2017.pdf.

[67] Msangi S, Rosegrant MW. Feeding the Future's Changing Diets: Implications for Agriculture Markets, Nutrition, and Policy. International Food Policy Research Institute (IFPRI) 2011;3.

[68] Shamshiri RR, Weltzien C, A. Hameed I, J. Yule I, E. Grift T, K. Balasundram S et al. Research and development in agricultural robotics: A perspective of digital farming. International Journal of Agricultural and Biological Engineering 2018;11(4):1–11.

[69] Lochner H, Beckmann C. Fachstufe Landwirt: Fachtheorie für pflanzliche Produktion: Planen, Führen, Verwerten und Vermarkten von Kulturen; tierische Produktion: Haltung, Fütterung, Zucht und Vermarkten von Nutztieren; Energieproduktion: Erzeugen und Vermarkten regenerativer Energie. 9th ed. München, Münster-Hiltrup: BLV-Buchverl; Landwirtschaftsverl; 2012.

[70] Herlitzius T, Grosa A, Bögel T. Bodenbearbeitungstechnik. Frerichs, Ludger (Hrsg.): Jahrbuch Agrartechnik 2018. Braunschweig: Institut für mobile Maschinen und Nutzfahrzeuge 2019;(30):1–11.

[71] Geoprospectors. Landwirtschaft / Geoprospectors. [October 26, 2019]; Available from: http://www.geoprospectors.com/de/produkte-leistungen/landwirtschaft/.

[72] Veris Technologies. Veris Technologies - The Sensors. [October 24, 2019]; Available from: https://www.veristech.com/the-sensors.

[73] Sharipov, G., Paraforos, D. & Griepentrog, H. W. Modeling and optimization of a no-till direct seeding machine. In: Ruckelshausen, A., Meyer-Aurich, A., Rath, T., Recke, G. & Theuvsen, B. (Hrsg.), Informatik in der Land-, Forst- und Ernährungswirtschaft 2016. Bonn: Gesellschaft für Informatik e.V. 2016:193–6.

[74] Sylvester Badua, Ajay Sharda. DEVELOPMENT OF A MACHINE VISION SYSTEM FOR REAL-TIME MEASUREMENT OF SEED SPACING AND SEEDING DEPTH OF CORN. In: 2018 ASABE International Meeting: American Society of Agricultural and Biological Engineers; 07292018.

[75] Meinel T. Sätechnik. Frerichs, Ludger (Hrsg.): Jahrbuch Agrartechnik 2018. Braunschweig: Institut für mobile Maschinen und Nutzfahrzeuge 2019;30:1–12.

[76] Dot Technology Corp. DOT - Farming Reimagined. [October 26, 2019]; Available from: https://seedotrun.com/.

[77] Fendt A. Fendt Xaver | Fendt FutureFarm - Fendt. [October 24, 2019]; Available from: https://www.fendt.com/de/xaver.

[78] Ecorobotix. Bekämpfen sie das Unkraut auf intelligente Weise – Ecorobotix. [October 24, 2019]; Available from: https://www.ecorobotix.com/de/.

[79] Lemken. Intelligente mechanische Unkrautbekämpfung: LEMKEN übernimmt Hacktechnikspezialisten Steketee. [October 29, 2019]; Available from: https://lemken.com/de/lemken-aktuell/news/detail/detail/intelligente-mechanische-unkrautbekaempfung/.

[80] Gaus C-C, Minßen T-F, Urso L-M, Witte T de, Wegener J. Mit autonomen Landmaschinen zu neuen Pflanzenbausystemen; 2017.

[81] Uppenkamp N. Mineralische Düngung. In Frerichs, Ludger (Hrsg.): Jahrbuch Agrartechnik 2018. Braunschweig: Institut für mobile Maschinen und Nutzfahrzeuge 2019;30:1–6.

[82] Blue River Technology. Blue River - See & Spray. [October 29, 2019]; Available from: http://smartmachines.bluerivertechnology.com/.

[83] Böttinger S. Mähdrescher. In: Frerichs, Ludger (Hrsg.): Jahrbuch Agrartechnik 2018. Braunschweig: Institut für mobile Maschinen und Nutzfahrzeuge 2019;30:1–17.

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