Whitepaper

Making agriculture sustainable with AI and autonomous systems while keeping safety in mind

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Data-based services using Artificial Intelligence (AI) are supposed to solve optimization problems and detect patterns, thereby helping us to achieve a more sustainable agriculture overall – through better decisions and optimally automated processes and machines. But can this work and can the risks be managed?

The transformation of agriculture and the integrative sustainability triangle

The quote from Heraclitus from around 2500 years ago (Heraclitus of Ephesus, ~520 - ~460 B.C.) "Nothing is as constant as change" fit then as it does today, and is currently emblematic of agriculture. Agriculture is facing many challenges, and there is even talk of a transformation of agriculture. At the moment, almost all types of agricultural enterprises are undergoing change. In animal husbandry, an upheaval is currently taking place regarding the existing husbandry conditions, and the focus is on appropriate animal welfare. However, many questions still remain open here, especially with regard to the forms of husbandry, including building regulations and how farms can realize all this (profitably). Furthermore, the impact of animal husbandry on the climate (e.g., manure output, methane emissions from ruminants) is being critically analyzed. Crop farming is also undergoing change, with increased (crop-related) challenges such as resistance to herbicides, tighter regulation of fertilizer use, or declining biodiversity. Overall, demands on agriculture are increasing and work processes are becoming more complex. In addition, numerous official environmental regulations, verification and documentation obligations must also be complied with nowadays [1].

Agriculture must meet ecological demands without neglecting economic feasibility and social aspects. The integrative sustainability triangle [2] illustrates the interplay and tension between ecological, economic, and social aspects (see Figure 1): If you pull on one corner of the triangle and hold on to the other two corners, tension is created. A crucial point in this tension is the weighting of the individual sustainability aspects, which are ultimately determined by the government and thus indirectly by society.

Autonomous systems as key to meeting competing sustainability goals

Digitalization and innovative technologies play a crucial role in bringing the competing sustainability goals closer together. Figuratively speaking, the square "social-ecological-economic" in Figure 1 can be drawn larger because of the expected technology leap and can thus cover larger portions of the individual sustainability aspects. Autonomous systems, in particular, hold enormous potential for making agriculture more sustainable (e.g., resource-conserving use of agricultural inputs with regard to climate and environmental protection). This makes it possible to continue producing high-quality and sustainable food, without causing unacceptably low profit margins for farmers or inacceptable food costs for poorer segments of society. The application areas in which autonomous systems hold great potential are described in the position paper of the working group "Adaptive Autonomous Agricultural Systems" published by the German Federal Ministry of Food and Agriculture (BMEL) [3]. In general, the areas of "crop cultivation", "animal husbandry", and cross-sector applications are listed. In crop cultivation, for example, autonomous field robots can be used – either individually or in swarms, depending on size – to remove weeds or to treat small areas (this is conceivable down to individual plants) selectively with fertilizer or crop protection products as needed. The first such robots are already on the market and are performing tasks such as seeding and mechanical weed control. According to Shamshiri et al. (2018) [4], rapid technological developments can be observed in the field of agricultural robotics.

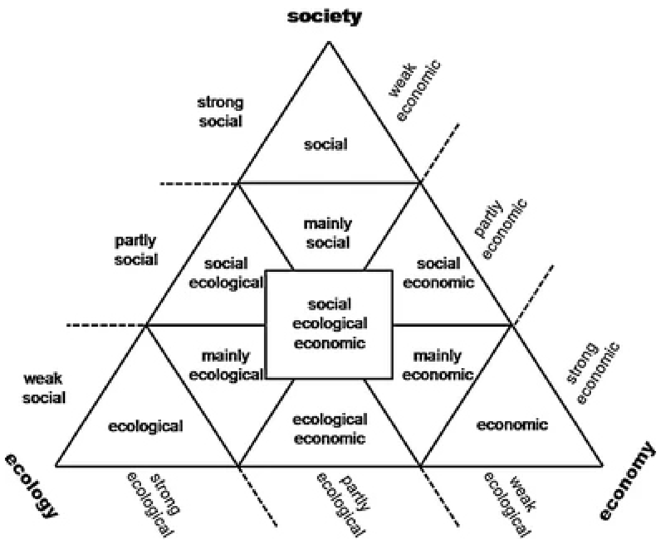

Figure 1: Integrative Sustainability Model [2]

Autonomous systems are not limited to field robots, but are also used in animal husbandry. Milking robots have been in use on many farms for quite some time already. In addition, feeding and animal control, in particular, offer potential for autonomous systems. Furthermore, autonomous systems are also finding their way into cross-sectoral areas, such as remote sensing and cooperation between machines. Another example is the mapping of the value chain by linking autonomous systems. Based on this, various optimization options are possible, such as dynamic adaptation to different situations.

One conceivable example in logistics is route planning that can dynamically adapt to different situations (congestion risk, road conditions, loading points, diesel consumption) by linking autonomous systems. Overall, in agriculture as well as in the entire value chain, autonomous systems hold great potential for producing food and feed more sustainably (in economic, social, and ecological terms).

Market potential of autonomous systems and safety as a major barrier to market entry

The usage potential of autonomous systems with a focus on crop cultivation was also investigated in the study by Dörr et al. [5] in 2019. Based on interviews with experts, it was predicted how high the market share of different levels of autonomy would be in relevant international markets by 2045. For the European market, for example, the second-highest level ("supervised autonomous") was predicted to account for a market share of over 80 %. With the exception of the African market, the market share of autonomous systems of the highest level ("entirely autonomous machine") was estimated to be around 10–50 % in 2045.

The experts cite the guarantee of safety as a major obstacle in this context. In line with this, a central recommendation for action in the BMEL position paper mentioned above [3] is the "development of new safety concepts and their manifestation in regulations and/or standards".

Definition of "autonomous systems" and levels of autonomy

In order to anchor the requirements and safety concepts for autonomous systems in regulations and/or standards, it is first necessary to clarify what autonomous systems actually are. However, current laws and guidelines such as the EU Machinery Directive and associated harmonized standards such as DIN EN ISO 12100 do not use the term "autonomous". Similar to "Artificial Intelligence", there are very different understandings of what an "autonomous system" is. Of course, clarification of the terminology does not only concern the application area of agriculture, but also other areas such as logistics or the military. Furthermore, this does not only affect one country or one economic area. On questions such as "What is the difference between autonomous and fully automated?" (also see the IESE blog post *"Autonomous or maybe just highly automated?"*), an intersectoral and international consensus is being sought, but there is as yet no universally accepted definition.

Autonomy is generally understood as a gradual concept. However, the way different levels of autonomy are defined differs. The SAE (Society of Automotive Engineers) levels in the automotive field map various aspects such as the role of the driver or the complexity of the driving task onto a one-dimensional scale. In the Autonomy Levels for Unmanned Systems (ALFUS) from the military domain, independence from humans is related to the complexity of the operational environment and the complexity of the mission (Figure 2).

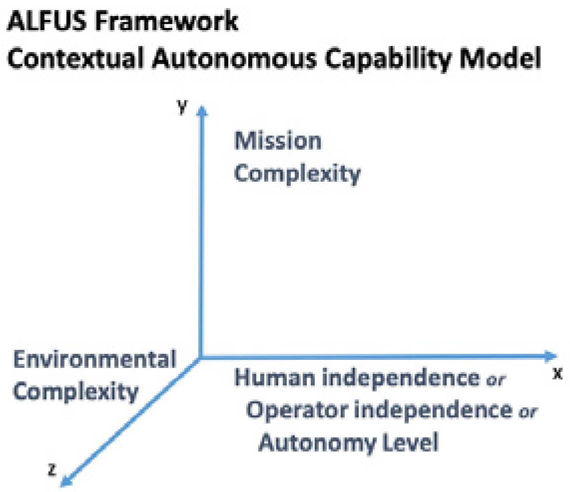

Figure 2: ALFUS Framework [6]

In the position paper of the BMEL working group "Adaptive Autonomous Agricultural Systems" [3], reference is also made to different levels of autonomy, and a potential standardization of the levels in the context of ISO 18497 "Safety of partially automated, semi-autonomous and autonomous machinery" [7] is envisaged. The draft of ISO 18497, which is currently under development, includes Table 1 below to help explain the distinction between partially automated, semi-autonomous, and autonomous [7]:

A function is here defined as an activity or behavior of a machine. "Steering" is given as an example. With regard to the term "automated", the following definition is provided by ISO 18497: "Technique, process, or system for operating and controlling machine functions by automatic means." There are inconsistencies in these definitions and they may need to be revised. First of all, the question arises as to whether the activity of a machine is not always automated, due to the fact that this activity is carried out by the machine. The complexity of the tasks "Implement driver's steering request", "Drive along a specified route", and "Find a suitable route and drive along it" differs significantly, of course. The higher the complexity of a task, the more difficult it is to automate it completely, i.e., to have it done entirely by a machine. This view fits in with the ALFUS taxonomy, which focuses on the complexity of the task or mission. Essentially, the question is whether the adjective "automated" can refer to a system or should not basically refer to something tangible like a system, but always to a task or a process, in order to express that the task or process is done completely or partially by a technical system. It is also confusing that “automated” is defined as “technique, process, or system…”, since “automated” is a property, whereas “technique”, “process”, and “system” are not properties.

The modes in Table 1 refer to the interaction with humans and are thus similar to the independence from humans in the ALFUS taxonomy (see x-axis in Figure 2). The complexity of the environment (z-axis in Figure 2) is not considered here.

Challenges regarding the safety assurance of autonomous systems

However, the operating environment is directly related to the challenges regarding safety. As long as humans keep an eye on the operating environment, recognize hazardous situations, and use simple functions such as braking to avoid inacceptable risks, it is sufficient to identify the functions that are necessary for safety and to address critical defects such as brake failure. Accordingly, DIN EN ISO 12100 calls for the identification of necessary safety functions and refers to the functional safety standards for the correct implementation of safety functions. For the agricultural sector, ISO 25119 and ISO 13849 are particularly relevant here. If humans are no longer responsible for recognizing hazardous situations, there are essentially two options. Either the operating environment is designed in such a way that the hazardous situations can no longer occur, or the system is enabled to recognize and deal with hazardous situations. An example of avoiding hazardous situations is a fence and a gate that brings all machines directly to a standstill when it is opened. The example illustrates that simple measures are often not possible from an ecological or economic perspective. This is why the safety assurance of autonomous systems often leads to more complex safety functions that recognize hazardous situations on their own and decide how best to control the risks in the current situation.

The basic idea of this “dynamic risk management” is applicable to any hazardous situation and risk and is not limited to safety risks. In the following, we will consider collision risks, as they often make up a large part of the risks. Accordingly, there are dedicated standardization initiatives such as ISO 21815 “Earth-moving machinery – Collision warning and avoidance”[8]. A key challenge in the implementation of dynamic risk management is the detection of objects and other aspects related to hazards and their risks, such as the detection of people in a stand of tall plants. One approach to improving awareness of risks in the environment is to share information. For example, a drone could fly ahead and share anything it detects from its bird’s eye view with autonomous agricultural machinery. Another approach is to use methods from the field of Artificial Intelligence, particularly Machine Learning methods.

Collaborative dynamic risk management

The application guide VDE-AR-E 2842-61 already takes into account the collaboration of systems for the realization of dynamic risk management. In part 3 “Solution Level”, the complete socio-technical working system is regarded and the development of a “runtime risk manager” (cf. 12.4) is considered. To enable cross-machine dynamic risk management, the systems must exchange safety-relevant information. In doing so, the safety integrity of the provided information must match the required safety integrity. As explained in the application guide, this can be done using machine-readable assurance cases based on the OMG standard SACM [9]. With this approach, the information receiver can assess whether the measures taken to eliminate failures are sufficient for the intended purposes and whether context assumptions made are true. Digital Dependability Identities [10] provide one option for implementing this approach.

<table>
<tr><th></th><th>Manual Non-Automated</th><th>Partially Automated</th><th>Semi-Autonomous</th><th>Autonomous</th></tr>
<tr><td rowspan="2">Functions</td><td colspan="3">Non-Automated</td><td></td></tr>
<tr><td></td><td colspan="3">Automated</td></tr>
<tr><td rowspan="2">Modes</td><td colspan="3">Manual Mode</td><td></td></tr>
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Table 1: Distinguishing aid for different degrees of automomy [7]

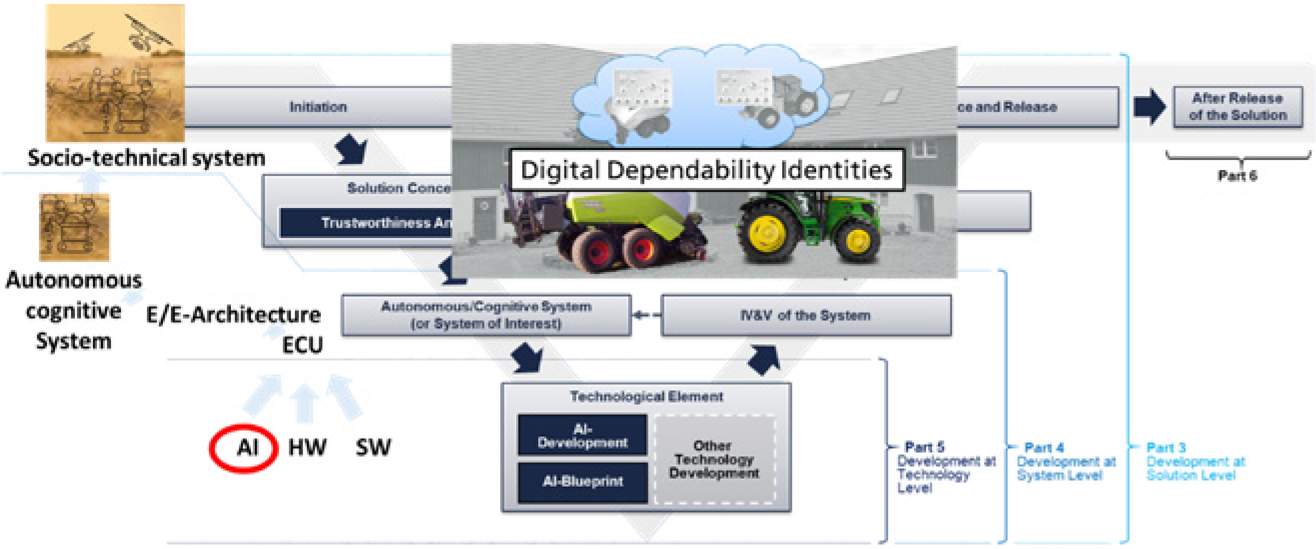


Figure 3 – The 3 levels of the VDE-AR-E 2842-61 "Development and Trustworthiness of Autonomous/Cognitive Systems" (modified)

The application guide also calls for dynamic risk management and other safety-relevant functionalities to be implemented using approaches from the field of Artificial Intelligence. Machine Learning approaches and data-driven models are particularly relevant in this context.

AI-based dynamic risk management

The output of data-driven models is inherently subject to uncertainties. According to the onion-skin model in [11], a distinction is made between three types of uncertainties:

(1) Uncertainty due to inherent limitations of the learned model

(2) Uncertainty due to limited input quality during application (rain, etc.)

(3) Uncertainty due to deviations between the modeled context and the application context

Uncertainties are thus situation-specific. Dynamic risk management takes these situation-specific uncertainties into account based on a component that estimates the uncertainties on a situation-specific basis during operation. Figure 4 illustrates this "Uncertainty Wrapper".

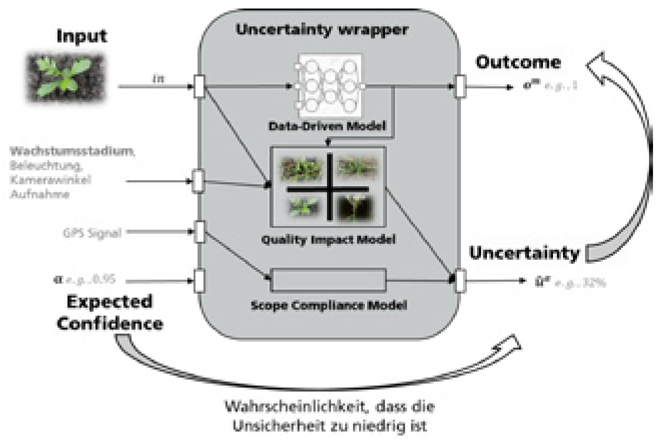
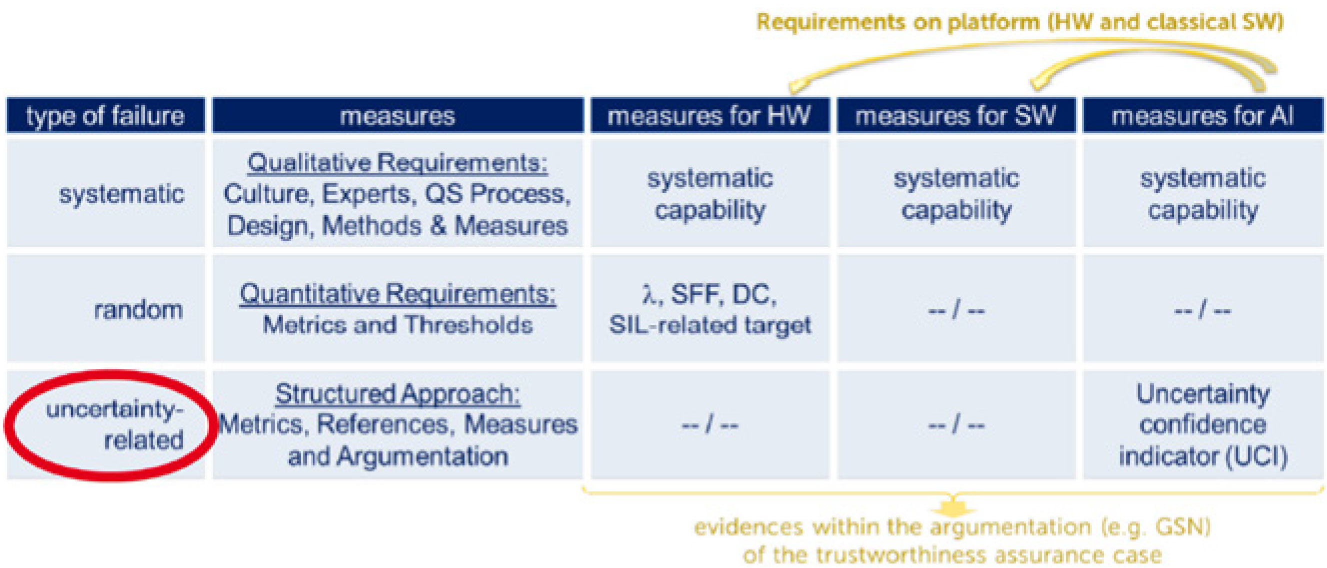


Figure 4: Uncertainty Wrapper (modified based on [11])

Influencing factors regarding the input quality are captured by additional inputs such as lighting or camera angle. A quality model uses these inputs to determine uncertainties due to input quality. A scope compliance model determines the uncertainties based on possible deviations between the modeled context and the application context. When it is clear that the system is not operating within its "Operational Design Domain", the uncertainty is set to 100%. As the uncertainty is estimated, it is necessary to specify with which level of confidence the estimation should be made. The greater the confidence required to ensure that the uncertainty is not underestimated, the more pessimistic the estimate must be.

Since typically not all failure modes are safety-critical, uncertainty refers to the existence of a specific failure mode. Dynamic risk management then deals with this failure probability in a situation-specific manner. One example of this management of uncertainties is described in [12]. Similar to the handling of failure probabilities for random hardware failures, threshold values are necessary here to determine what is sufficient. In this respect, the VDE-AR-E 2842-61 standard describes the idea of introducing a failure rate λ_{AI}, arguing that as more knowledge about AI technologies is gained, it might be feasible to define a real failure rate λ_{AI} associated with the AI element. Furthermore, it introduces a new failure class in addition to random hardware failures and systematic failures. As depicted in Figure 5, these "uncertainty-related" failures are to be addressed with different approaches.

Dynamic risk management is only a technical mechanism for assuring the safety of autonomous systems (Safety and Artificial Intelligence). Many other issues need to be considered as well. In order to deal with all issues uniformly and address safety (as well as other aspects of trustworthiness), VDE-AR-E 2842-61 recommends the use of assurance cases. It is still an open research question how assurance cases for AI components should be structured and developed, but there are already different approaches, like AMLAS [13] or the approach of Kläs et al. (2021) [14] from the project ExamAI [15]. Currently, efforts are under way in the research project LOPAAS [16] to consolidate these approaches and make them available for standardization activities. This concerns, in particular, the standardization activities on cross-sector documents such as the technical report "ISO/IEC AWI TR 5469 Artificial intelligence — Functional safety and AI systems" [17] in the context of IEC 61508 and the already mentioned VDE-AR-E 2842-61.



type of failure	measures	measures for HW	measures for SW	measures for AI
systematic	Qualitative Requirements: Culture, Experts, QS Process, Design, Methods & Measures	systematic capability	systematic capability	systematic capability
random	Quantitative Requirements: Metrics and Thresholds	λ, SFF, DC, SIL-related target	-- / --	-- / --
uncertainty-related	Structured Approach: Metrics, References, Measures and Argumentation	-- / --	-- / --	Uncertainty confidence indicator (UCI)

FIgure 5: "Uncertainty-related" failures, VDE-AR-E 2842-61

Summary and Conclusion

In summary, autonomous systems offer great potential to achieve the sustainability goals in agriculture more effectively and without compromise. The key to fully exploiting this potential of autonomous agricultural systems are innovative safety solutions. The underlying safety concepts are described in numerous publications and an application guide. It is difficult to predict how long it will take for these concepts to be established in practice, as the application-specific implementation of the concepts involves pioneering work.

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