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Gaia-AgStream: An Explainable AI Platform for Mining Complex Data Streams in Agriculture

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Abstract. We present a position paper about our concept for an artificial intelligence (AI) and data streaming platform for the agricultural sector. The goal of our project is to support agroecology in terms of carbon farming and biodiversity protection by providing an AI and data streaming platform called *Gaia-AgStream* that accelerates the adoption of AI in agriculture and is directly usable by farmers as well as agricultural companies in general. The technical innovations we propose focus on smart sensor networks, unified uncertainty management, explainable AI, root cause analysis and hybrid AI approaches. Our AI and data streaming platform concept contributes to the European open data infrastructure project Gaia-X in terms of interoperability for data and AI models as well as data sovereignty and AI infrastructure.

Our envisioned platform and the developed AI components for carbon farming and biodiversity will enable farmers to adopt sustainable and resilient production methods while establishing new and diverse revenue streams by monetizing carbon sequestration and *AI ready* data streams. The open and federated platform concept allows to bring together research, industry, agricultural start-ups and farmers in order to form sustainable innovation networks. We describe core concepts and architecture of our proposed approach in these contexts, outline practical use cases for our platform and finally outline challenges and future prospects.

Keywords: Explainable AI · Sensor Networks · Distributed Systems · Uncertainty Management · Complex Networks · Machine Learning · Anomaly Detection · Root Cause Analysis · Knowledge Graph · Data Quality · Agroecology · Carbon Farming · Biodiversity · Data Fusion.

1 Introduction

In order to adapt to climate change and preserve biodiversity, the agricultural sector and in particular farmers can do a lot by changing their practices, but they need support on decision making for strategic aspects as well as in their daily business. Today, farmers do not aim to increase the physical productivity but rather try to preserve, or even increase, the economic productivity of their work. To achieve this goal, they embarked on the path of agroecology as a holistic ecological concept which aims to maximize biodiversity on a functional level in order to strengthen biological self-regulations rather than resorting to external inputs and management activities. This is based on a number of key principles:

1. Increasing the recycling of biomass and achieve a balance in the flow of mineral elements.
2. Providing the most favorable soil conditions w.r.t. growth of plants, by maintaining a level of organic matter and high biological regulation mechanisms.
3. Minimizing the loss of nutrients from the circuit system and form relatively closed loops rather than open streams.
4. Improving the functional biodiversity of plants and animals, natural and domestic, cultivated or raised, above and in the ground, in order to strengthen the *immune system* of agricultural systems.

Thus, agroecology as a holistic approach requires contributions from farmers, contractors, consultants, research, education and so forth. We focus on carbon farming and biodiversity as the most important aspects in order to fight and adapt to climate change and contribute to the preservation of biodiversity. We need to strengthen the resilience of our agricultural economy and accelerate the adoption of sustainable production methods.

On a technical level, we already see Gaia-X (<https://www.gaia-x.eu/>) [12] as a perfect fit to our vision of a federated learning platform. However, the Sovereign Cloud Stack (SCS) that is currently developed by the 22 founding members of the AISBL only covers the interoperability on infrastructure level. Even though we have massive amounts of satellite images, farm management data, drone videos and other sensor readings, which all contribute to the big data treasure in agriculture, there is still too little utilization of such data in terms of modern AI components which find their way into software and hardware products for farmers and farm equipment manufactures as well as agricultural software companies.

In this position paper, we present a concept for an AI and data streaming platform for the agricultural sector. The goal of our proposal is to support agroecology in terms of carbon farming and biodiversity protection by providing an AI and data streaming platform called *Gaia-AgStream* that accelerates the adoption of AI in agriculture and is directly usable by farmers as well as agricultural companies in general. The technical innovations we propose focus on smart sensor networks, unified uncertainty management, explainable AI, root cause analysis and hybrid AI approaches. With this, biodiversity and other complex information can be monitored in real-time – to be utilized for guiding agronomic decisions farmers have to take in their daily business as well as for strategic planning.

The rest of the paper is structured as follows: Section 2 discusses related work. After that, Section 3 presents our Gaia-AgStream approach as well as the targeted use cases. Finally, we conclude in Section 4.

2 Related Work

Below, we first present related projects, before discussing sensor networks and explainable AI as core concepts for our proposed approach.

2.1 Related Projects

As our proposal brings together AI and data streams in agriculture, there are different related open source projects which focus on one or several of these aspects and we can only list some of them. Recently, the Linux foundation has launched the open source agriculture infrastructure project *AgStack*⁶ in order to offer a secure digital operating system for the agricultural industry. *farmOS*⁷ is an open farm management software which offers a web-based application for management and planning.

There is a widely used open-source technology stack for handling data streams, e. g., Apache Kafka, Apache Spark, RabbitMQ, etc. Approaches like Kafka or Apache Flink not only allow to manage data streams at scale, but also support data stream processing and together with common AI frameworks like TensorFlow or PyTorch build a solid technological foundation for state-of-the-art AI projects for data streams. In particular, Kafka-ML aims to fit TensorFlow and Kafka streams into one user-friendly web interface and River merges *creme* and *scikit-multiflow* into a single python library for machine learning on data streams.

None of these frameworks includes a seamless uncertainty management from initial data generation to AI output consumption by users. Approaches like MLOps help to emphasise the importance of data for AI applications during training and operation by keeping track of every artefact. Projects like KubeFlow or MLFlow help to automate pipelines for training and deployment of AI models in multi-cloud and edge-computing scenarios.

Unfortunately, none of these efforts has changed the fact that still about 80% of the time it takes to bring an AI model to production is spent on working with the data due to data quality issues. Thus, even initiatives like Gaia-X which contribute to the accessibility of data may have a limited impact on the adoption to AI without focusing on data quality.

Gaia-X is a European initiative for fostering the digital sovereignty in Europe. The most important aspect related to our proposal is the aim to establish sovereign data exchange for all companies, organizations and citizens within the Gaia-X framework. This overall goal is realized in many different domain specific projects which cover basic building block for data exchange like interoperability and the harmonization of standards.

⁶ <https://agstack.org/>

⁷ <https://farmos.org/>

A highly visible project within Gaia-X is Agri-Gaia which aims to build an AI platform for the agricultural industry, in order to make AI accessible for the all participants in the domain, especially small and medium enterprises. Agri-Gaia and its consortium has founded the agriculture domain within the German Gaia-X hub. Another project related to Gaia-X is NalamKI which focuses on fostering sustainable production methods by means of AI and the aggregation of sensor and machinery data in one central platform. A core aspect here is data sharing along the value chain in order to create new innovation networks. Further contributions to Gaia-X originate from Soil-X which focuses on soil data with respect to accumulation, harmonization and utilization of such data.

One key aspect of Agri-Gaia with respect to providing data for AI at scale is the generation of synthetic data for training AI models in order to leverage existing high-quality real data. Here, we want to complement this line of work by developing a uniform uncertainty management embedded in the proposed AI and data streaming platform to support the generation of ‘AI ready data’ and find an application-agnostic data quality indication, cf., [13, 14, 28] for according related work about uncertainty estimation, architecture concepts and robust self-optimization. The importance of handling uncertain data is inherent to AI applications, but the current balance between the effort for handling data and tuning the model puts a disproportional weight on data handling. This includes standard tasks like data collection, analytic, harmonization, aggregation and versioning. The goal of all of these activities is to ensure and enrich the quality of the data which is ultimately used for training AI models. This need for high quality data is especially hard to meet in applications which include federated or distributed learning, e.g. in edge computing scenarios with limited or only partial connectivity. In such cases, there is no human operator or observer who maintains the edge unit and thus, the systems needs to operate fully autonomous including all aspects of data preparation. But even in cloud computing scenarios the automation of data processing is the best lever to foster AI applications.

2.2 Sensor Networks

Wireless Sensor Networks (WSN) consist of a large number of small, cheap, resource - and power-constrained devices. Depending on their sensing task, they are equipped with one or multiple sensors [2]. These devices form automatically a local wireless network that collects the data at one or multiple sinks. A sink is typically connected to the Internet. The purpose of the devices in such a distributed system is the environmental sensing of physically measurable phenomena, like temperature, relative humidity, or soil moisture. Sometimes more powerful nodes even perform audio and video sensing. However, the applied devices are typically low-cost and thus resource constrained. However, this makes them suitable for large-scale and long-term deployments. The sensing accuracy of each single device is usually limited. However, this limitation is compensated by multiple collaborating devices. Thus, WSNs allow for continuous monitoring, providing sensor information at high temporal as well as spatial resolution.

WSNs in agriculture have been a research topic for more than one decade now, cf. [26]. Here, technological advancements continuously reduced the physical size and costs of the devices. Nowadays, WSNs complement existing monitoring systems in the context of precision agriculture with ground-based information advancing productivity and sustainability. Possible applications range from site-specific irrigation, fertilization, and crop treatment, to disease control as well as horticulture and animal monitoring [27]. WSNs are usually integrated into Farm Management and Information System (FMIS) and IoT platforms (cf. e. g., [32]).

For a large-scale environmental monitoring, often a large number of sensors is required. From an economic perspective, the price of the individual sensors is crucial for the Return on Invest (ROI). Thus, there is a trend to reduce the number of devices in sensor networks in real deployments and complement them by remote sensing, e. g., based on satellites or drones. The WSN provides in-situ data to calibrate the remote sensing data. In addition, information gained in-situ via a WSN can be transferred to larger areas using remote sensing data.

2.3 Explainable AI and Decision Support

Recently, the area of explainable AI [17] (XAI) has emerged as a prominent paradigm to enhance decision support, which is particularly relevant in economically and environmentally sensitive applications and the use cases we target in Gaia-AgStream. [3] While there are several solutions providing AI and machine learning in agricultural contexts, typically black-box models are applied, which make it difficult to validate their analytics insights, predictions, recommendations, and root causes those are based on. In general, intransparent methods and models make it more difficult to spot mistakes, as algorithmic methods can potentially learn “bad habits” from improper data. If the data used for constructing AI models, e. g., contains misleading or wrongly classified examples, then it is highly likely that the resulting model incorporates specific biases and data artefacts which can lead to wrong conclusions. In addition, in the case of black box models the applied models and their decisions are then not understandable for humans, which can lead to wrong and/or bad decisions. Essentially, those can then not be considered as actionable. XAI aims at providing explanations for the models, their analytics insights or their predictions and recommendations.

In the case of Gaia-AgStream we target this regarding monitoring and anomaly detection, e. g., by adapting and building on interpretable models and detailed root cause analysis methods, e. g., [1, 6, 10]. For recommendation, e. g., specific (historic) example cases can be provided for justification, or interpretable patterns summarizing typical (causal) influence factors can be presented. This also relates to, in particular, explanation-awareness [5, 8] and XAI in such contexts [17, 29, 31], recommendation methods on complex feature-rich data, modeled as complex networks, e. g., [16, 21, 25, 30], and interpretable models for deep anomaly analytics, covering anomaly detection, explanation and providing interpretable models cf., [4, 7, 15, 34].

In addition, we furthermore aim at proposing deep learning approaches able to leverage heterogeneous information sources (multi-source satellite images, sen-

sors, and more) in order to produce accurate estimations regarding the soil carbon and the biodiversity of a certain area, cf., [20,23]. The eventual use of sensors also opens up to the use of advanced geometric deep learning techniques, i. e., graph convolutional networks able to exploit non-euclidean structures in the data, such as network graphs, e. g., [9,33]. Note that the use of advanced deep learning techniques allows to work on data fusion at a feature level. Classic data fusion approaches generally include early fusion (i. e., integrating the different sources of information at the beginning of the process, in order to obtain a single dataset that can be used as input for the machine learning algorithm) and late fusion (i. e., aggregating the predictions from models associated with each data source into a global prediction). Devising advanced deep learning architectures, e. g., [18,19,22,29] able to deal with multi-source data allows to extract an optimized data representation for each source (e. g., representation learning on multi-branch architectures, where each branch deals with a data source), producing optimized features that are then used as input of the final step of the process, e. g., classification or regression.

3 The Gaia-AgStream Approach

The scope of the problem we tackle can be highlighted using biodiversity as an example. The measurements for biodiversity are getting better and better, still further improvements need to be done in order to get AI ready and actionable data which leverage the existing data sources in order to get reliable long-term predictions and near real-time data for day-to-day recommendations. These recommendations need to be based on trustworthy data and explainable AI in order to get the acceptance of farmers, farm equipment manufactures and other partners in the agricultural domain like consultants and contractors. Thus, our goal is to foster trust and transparency along data processing pipelines and in complex innovation networks.

3.1 Proposed Approach

Gaia-AgStream provides an AI data stream processing platform as an infrastructure component within Gaia-X and demonstrates the benefits of the platform in an agroecology use case that comprises the development of ready to use AI components together with a smart sensor network management. The proposed approach, connected to exemplary case studies and services provided is depicted in Figure 1. The center of our activities is the farmer and his need to master carbon farming and support biodiversity. Our platform provides smart sensor networks for farmers as well as explainable AI recommender systems. Overall, the platform builds an innovation network by connecting traditional agriculture companies, AI startups and farmers in order to share and exchange data and AI-models. The core innovation and knowledge distribution detailing the technical foundation of Gaia-AgStream is depicted in Figure 2 – focusing on the

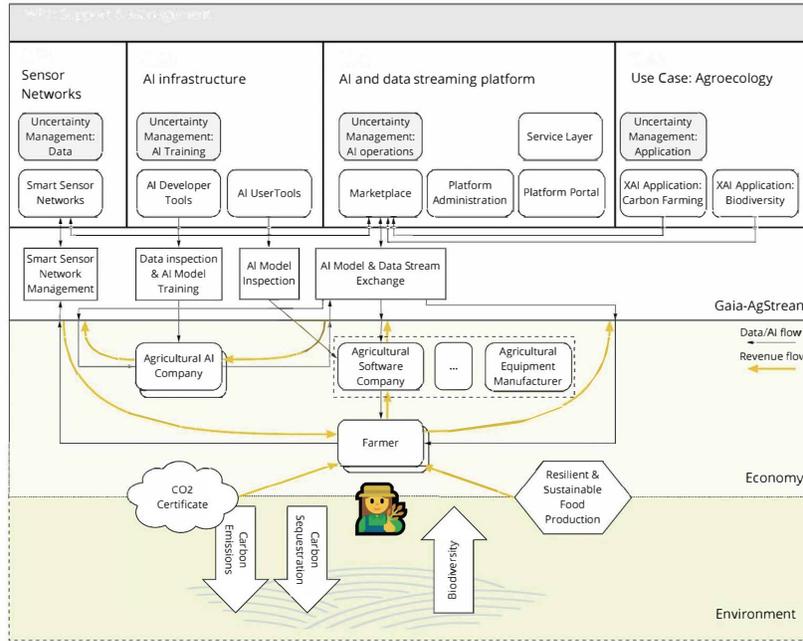


Fig. 1. Overview: Schematic visualization of the overall technical and economic solution, and the respective case studies/application areas.

dynamic, uncertain causal knowledge graph model which integrates dynamic and uncertain data, and enables AI-based recommenders and analytics.

Our platform is in line with the currently founded project Agri-Gaia and aims to extend this AI infrastructure project by providing capabilities for data stream processing and the corresponding AI components for learning from data streams. Data streams are inherently different to handle than data set as data needs to be prepared and used for learning incrementally and in production. In the hybrid on-line and off-line connection scenarios we are facing in agriculture, this rises the need for IoT solutions that allow to learn on the edge or on device in order to minimize the data traffic and build economically viable solutions. Learning from data stream on the edge or device requires a holistic approach to data analysis, preparation and monitoring as there is no operator which can observe and handle the learning process as it is common in cloud computing. Edge computing here may apply to individual sites of a larger farm, machinery or small farms as they usually have limited computing resources. The challenge here is to allow for an easy deployment and mostly independent learning of the edge units while at the same time support farms by means of centralized monitoring and reasoning capabilities offered by the platform. This requires the edge units to provide meta data about their learning processes and consume appropriate data, parameter or hyperparameter sets in order to accelerate and

steer the learning process in a federated way where different edge units working together in the same field or at the same farm can share their insights about e. g., anomalies, and validate each other’s data and learning outcomes.

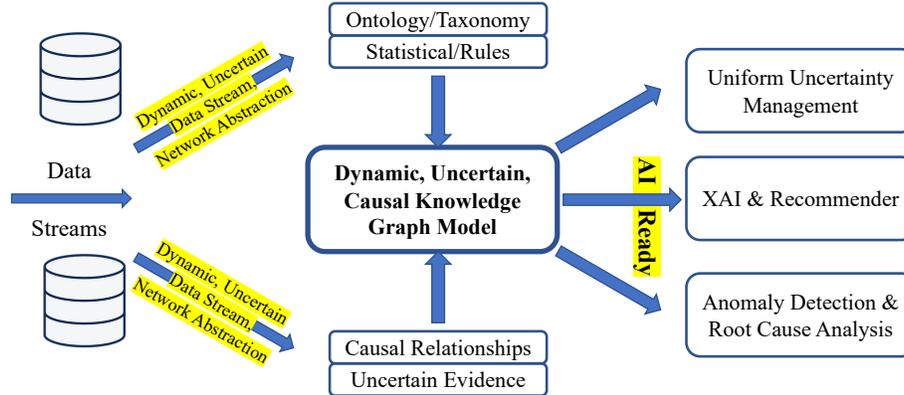


Fig. 2. Overview: Schematic visualization of the core innovation and knowledge distribution for the technical foundation of Gaia-AgStream

Validating data from different sources like satellite, machinery and field sensors for building useful recommendations to farmers is only possible by understanding how the farmer plans his activities, executes the plans and reflects about the outcome of his work. The practices on each farm tend to be unique although best practices spread word and become adopted by a community. Therefore, one contribution of our project will be an AI component capable of building a knowledge graph which reflects the options and practices for individual farms by analyzing the farm management data and fuse this data with existing databases and meta data models, e. g., within the Agricultural Data Space.

In order to get to useful recommendations for farmers trust and transparency are of paramount importance. From a platform point of view the core aspects we can provide here are explainable AI components which get trained and evaluated on high quality data. Data quality is one of the most important topics in any machine learning project, but the systematic to assure data quality in every step of the processing pipeline is still poorly supported by standard tools. Our goal is to make data quality a cornerstone of the platform by ensuring a transparent and unified uncertainty handling from measurement to recommendation, prediction or any other kind of AI application. Networks of smart sensors are best to showcase this capability of the platform as we can cover the whole data flow from measurement where data quality is rated based on physical properties of the signal, over to preprocessing and analysis on the device or edge where data quality becomes more influenced by master data about expected operating conditions as well as complex analysis e. g., to detect certain species in pictures

or from audio recordings and the corresponding model uncertainties. For federated learning approaches, this uncertainty modeling is essential meta data which allows to fuse data based on relevance rather than mass and make informed deep dives into individual decisions from models and AI components.

Hence, the sensor network management system we are going to build as part of the platform will not only allow for an easy deployment of complex algorithms to sensor nodes, but also ensure the data quality monitoring from an application agnostic point of view, i. e., via sensor health monitoring, signal to noise estimations, intra network validation of data with sufficient redundancy etc. The goal is to generate data which is ‘AI ready’ and therefore can directly be used for AI components in training and evaluation.

3.2 Agroecology Use Cases

For Gaia-AgStream the focus is on defining requirements for the overall platform development including the relevant basic AI components and services as well as the preparation and start of the field tests. In addition to that, we foresee a blended iterative approach for the development of the XAI components for carbon farming and biodiversity. This allows us to validate and refine the requirements from the technical perspective based on the insights from carbon farming and biodiversity. Further, stemming from the experience gained in working on carbon farming and biodiversity we add the use case level perspective to our unified uncertainty management. The hybrid XAI approach we follow allows to easily integrate prior knowledge of individual farmers about their fields, practices or crops. This will help us to interact with the community we build and get a common understanding about how the XAI components need to behave when integrated into end-user products. The application of the platform is exemplified via two use cases, which address those two of the most urgent topics of our time.

Carbon Farming Carbon farming refers to agricultural methods that aim at reducing the amount of atmospheric carbon by capturing carbon in the biomass within the soil and/or favoring stocking carbon in crop roots and leaves. In addition to carbon emission reduction, which already is a main target for sustainable agriculture, this can favor both plant growth and reducing use of fertilizers. Thus, this contributes to enhancing or at least preserving biodiversity in target fields.

The goal of this first use case of our proposal is to learn new rules that can help farmers in enhancing their carbon farming approaches. Personalized recommendations based on background knowledge but also on processing heterogeneous data collected from target fields will be provided. These rules allow farmers to change their practices not only with respect to capturing carbon in the soil, but also for process optimization and thus, the reduction of carbon emissions (e. g., reducing fuel consumption, change crop rotation, change soil preparation steps, etc.).

Biodiversity Our planet is losing biodiversity at an unprecedented high rate [24]. Thus, there is an urgent need to measure the impact of agriculture on biodiversity. By doing so, biodiversity can be one factor in the decision process of individual farmers about their fields, practices or crops.

There are different methods for determining biodiversity [11]. These methods include measuring bird richness, mammal richness, keystone species, etc. WSNs using audio and video sensing can measure the raw data to derive these parameters using sophisticated AI based data fusion. In the end, we need to identify and count the different animals. The AI components developed within Gaia-AgStream will enable us to do this and, thus, measure the biodiversity. Based on these measurements we can support continuous improvement cycles which include XAI recommender systems and enable the farmers to seamlessly integrate biodiversity considerations into their strategic planning and daily routines.

4 Conclusion

In this position paper, we presented Gaia-AgStream – an explainable AI platform for mining complex data streams in agriculture; it integrates explainable AI on complex data as a core approach, enabling smart analytics and decision support – being exemplified via two uses cases in agroecology. We discussed the relevant core concepts, and outlined the platform by sketching its technical architecture.

Our platform and sensor network management address key success factors for the agricultural domain in Europe which is dominated by SMEs which cannot afford to invest in AI capabilities on a large scale or have no inhouse AI resources at all. We provide the means to simplify the development and deployment of AI components and have a special focus on data streams as they are key to build recommendations based on near real time data and act accordingly. The crisis prevention mechanisms to fight climate change and biodiversity will become effective on larger time scales, but need the continuous monitoring and care taking in every action we take. Thus, the technology we are providing for our agroecology use case can seamlessly be applied to other scenarios which pose similar requirements.

The sensor network management system offers farmers the ability to create value for their own practices and further commercialize their data by sharing it with AI technology providers which use the data to build and refine their AI components. Ultimately, the platform is going to build a sustainable innovation and data cycle between farmers, AI providers and other stakeholders. The application of IoT and Edge computing in agriculture is a growing market with excellent perspectives for AI applications.

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