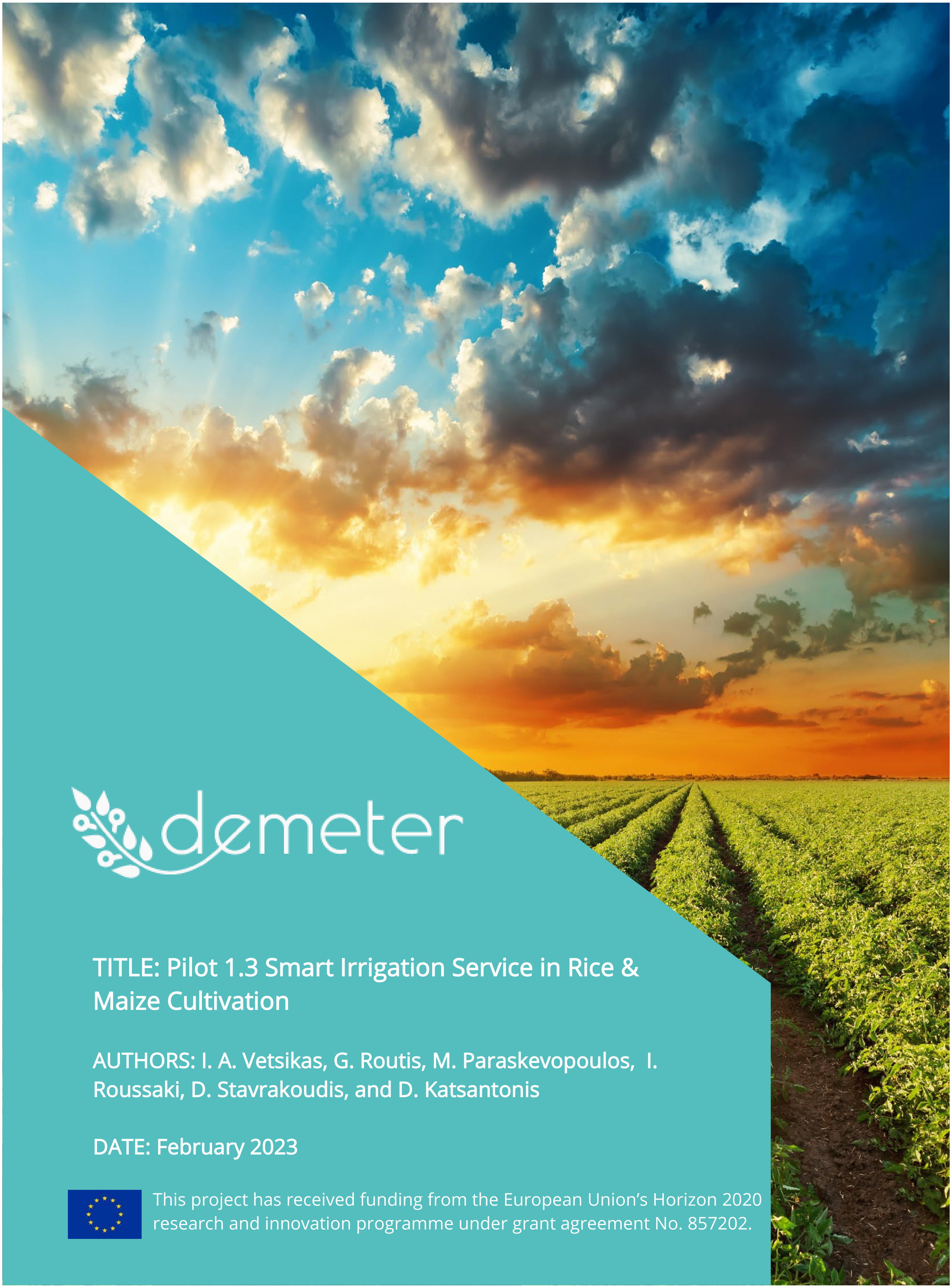

demeter

TITLE: Pilot 1.3 Smart Irrigation Service in Rice & Maize Cultivation

AUTHORS: I. A. Vetsikas, G. Routis, M. Paraskevopoulos, I. Roussaki, D. Stavrakoudis, and D. Katsantonis

DATE: February 2023

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 857202.

Pilot 1.3 Smart Irrigation Service in Rice & Maize Cultivation

1 Introduction

DEMETER aims to lead the Digital Transformation of the European agrifood sector based on the rapid adoption of advanced technologies, such as Internet of Things, Artificial Intelligence, Big Data, Decision Support (DSS), Benchmarking, Earth Observation, etc., to increase performance in multiple aspects of farming operations, as well as to assure the viability and sustainability of the sector in the long term. It aims to put these digital technologies at the service of farmers using a human-in-the-loop approach that constantly focuses on mixing human knowledge and expertise with digital information. DEMETER focuses on interoperability as the main digital enabler, extending the coverage of interoperability across data, platforms, services, applications, and online intelligence, as well as human knowledge, and the implementation of interoperability by connecting farmers and advisors with providers of ICT solutions and machinery.

DEMETER focuses on the deployment of farmer-centric, interoperable smart farming-IoT (Internet of Things) based platforms, to support the digital transformation of Europe's agri-food sector through the rapid adoption of advanced IoT technologies, data science and smart farming, ensuring its long-term viability and sustainability.

Twenty real-world pilot projects, grouped into five pilot clusters, are running within DEMETER to demonstrate and evaluate how agricultural innovations and extended capabilities benefit farmers, technology providers, and society. The topics, scope and size of the pilots are diverse, from saving resources, such as water and energy, to a more environmentally compatible crop management with reduced application of fertilisers and pesticides, to improved animal welfare and the tracing of complete supply chains.

This white paper describes the pilot 1.3 Smart Irrigation Service in Rice & Maize Cultivation. This pilot aims to improve the management and automation of rice irrigation, along with nitrogen zonal fertilisation. Maize is also an important crop for rice growers, as it is included in the majority of rice crop rotation systems—at least once every three years. Therefore, the pilot will also improve the management of both water and fertilisation in maize crops. The pilot was deployed in Greece in one main site managed by ELGO, as well as in several farmers' fields around the Central Macedonia region.

2 Importance of digital agriculture

Food security is of paramount importance due to the global population increase and in view of unpredictable events that can occur, such as the Ukraine crisis that has disrupted the supply of wheat and other crops. It is therefore necessary to increase the yields from agricultural land taking advantage of the newest technologies, in a sustainable manner that does not overuse resources such as water or other nutrients. EU policies favor the exploitation of IoT technologies in the agricultural domain (smart agriculture). Furthermore, EU also promotes the creation of a digital single market "ensuring that the European economy takes full advantage of what digitization offers".[1]

In view of these drivers and considering also the proliferation of IoT devices and advances in AI, IoT, and big data technologies, the DEMETER H2020 project aims to promote the rapid adoption of these advanced technologies in order to increase performance in multiple aspects of farming operations, as well as to assure the viability and sustainability of the sector in the long term. Twenty real-world pilot projects, grouped into five pilot clusters, are running within DEMETER, together with additional applications initiated through open calls, in order to demonstrate and evaluate how agricultural innovations and extended capabilities benefit farmers, technology providers, and society.

This white paper presents pilot 1.3, which aims to improve rice and maize yields, while reducing the resources used. More specifically, as will be presented later in this document, the goal is thus to use digital agriculture and IT technologies in order to reduce the consumption of resources (water and fertilizer by 15%) while maintaining the salinity of the water used to irrigate the rice below a critical threshold (under 3 dS/m); which will ensure that the yield remains optimal despite the reduced usage of resources.

There are however some barriers that hinder the adoption of digital solutions by farmers. The most prevalent of these are: the costs of the infrastructure, the lack of the initial skills required to used them, the reluctance to share their data and data

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[1] https://digital-strategy.ec.europa.eu/en/policies/strategy-data

privacy concern in general, as well as inadequate internet connectivity in rural areas; for example; sms was used to send messages to the farmers about the need to irrigate their rice fields.

3 Pilot Overview

Challenge

Rice is a high-input cultivation, especially in terms of irrigated water needs. Rice farmers frequently crop-rotate with maize, which also has substantial needs for irrigated water during the cultivation season. Current irrigation systems, especially for rice, are mainly based on farmers' experience and make suboptimal use of water, increasing the cultivation's cost, energy consumption particularly and the environmental footprint.

Aim

Pilot 1.3 aims to improve the management and automation of rice irrigation, along with nitrogen zonal fertilisation. Maize is also an important crop for rice growers, as it is included in the majority of crop rotation systems—at least once every three years. Therefore, the present pilot will also improve the management of both water and fertilisation in maize crop.

Where the pilot is being deployed and pilot partners

The pilot will be deployed in one main site in Greece and in several locations around Central Macedonia regions:

- ELGO Experimental Station of approximately 50 ha at Kalochori area (40°37'4.41"N, 22°49'54.19"E), Thessaloniki, Greece. This will be dedicated to both rice and maize crops, where the smart irrigation system will be deployed, tested and validated.
- More than 10 farmers in the same area of Kalochori and another 10 farmers in other areas were involved, in order to cover a variable rice and maize environment. These farmers dedicated fields suitable for testing according to ELGO's and ICCS's plan.

ELGO-DEMETRA is a research organization that promotes innovation and research on agriculture, aiming towards the modernization and development of Greece's agricultural sector. ELGO provides its expertise on agriculture research, developed a number of enablers to be integrated. Furthermore, it provides the liaison with the farmers on whose field the solutions were deployed, and leads the deployment and integration of these solutions.

The Institute of Communication and Computer Systems (ICCS) supports the research activities, the deployment, realization and growth of the research priorities of the school of Electrical and Computer Engineering of NTUA. In this pilot, ICCS provides technical expertise through the development of AIM and several enablers that are used in this pilot.

Solution / Innovation

Demeter's solutions provide the farmer, through the use of AI and IoT technologies, with decision support tools on how to irrigate and fertilize their crops. More specifically, customised in-field sensors are used for determining rice irrigation needs and remotely controlled water electrical valves are employed for automatically optimising the irrigation. Additionally, remote sensing imagery and inputs from meteorological stations are used for determining the irrigation needs of maize crops. Sub-parcel nitrogen fertilisation needs are estimated through UAV and satellite imagery, leading to optimal fertiliser use via variable rate application machinery. The data integrated are diverse, coming from a specialised, in-field salinity and water height IoT sensor, meteorological stations, UAV-collected multispectral and thermal imagery, as well as satellite imagery (both Sentinel-2 and commercial very-high-resolution images).

Key Benefits

The pilot achieves standardised crop production and improves the efficiency in the water and nitrogen fertilisation savings. Therefore, this decrease the carbon and, in general, the environmental footprint of both crops (rice and maize). Apart from the immediate benefits, this also adds a level of long-term investment security, especially in view of probable changes in water use strategies/policies due to the impact of climate change and the need to reduce (and optimize) the use of resources.

Image 1-3 Pilot in use

4 DEMETER Integration

Initially we describe AIM the common model developed so as to represent the various data exchanged within DEMETER apps, as well as its usage and the data wrappers developed for this pilot, then we describe the various enablers developed, and finally we present very briefly how all these are integrated into the three services that has been provided for this pilot.

<u>Agriculture Information Model (AIM) – Data Wrappers and AIM usage in the pilot</u>

The AIM model was developed within the DEMETER project as the common data model that all enablers should use to exchange data between them and thus facilitate interoperability between existing and new systems and enablers. The AIM is based on the NGSI-LD format[2] and contains ontologies for general terms, then domain specific ones, and then ones created for specific pilots. The modules comprising the AIM domain layer have been created by reusing well-known ontologies and models related to the agri-food sector. Thus, AIM is influenced and

[2] https://ngsi-ld-tutorials.readthedocs.io/en/latest/index.html

aligned with the best-known ontologies in the agri-domain, such as the FIWARE Agri-Food data model, Saref4Agri, FOODIE, ADAPT, INSPIRE, and uses terms from AGROVOC3 and other more general ontologies, such as SSN or the OGC geo-data. By providing this common model and by reusing ontologies and models, AIM enables semantic interoperability between existing and new enablers (and systems).

Now, the lowest layer of AIM, namely the Pilot-Specific ontologies, defines ontologies that cover the needs of the various pilots providing tailor-made ontologies that handle concepts that are not part of the aforementioned best-known ontologies that AIM was aligned with (in the AIM cross-domain and domain specific layers). For example, two of these extensions are created to serve—among others—our pilot: nutrient Monitor and fertilization Process. The nutrient Monitor ontology models information that concerns traits related to morphological or physiological condition like leaf Nitrogen, lea fLength, leaf Anatomy and wood Carbon as well as several vegetation indices. Also, several data properties have been added, concerning more crop traits and vegetation indices like ndvi and biomass. The fertilization Process ontology contains information concerning the whole fertilization cycle with properties like expected Harvest, spraying Conditions, nitrogen SoilIntake, nitrogen Concentration, nitrogen Content, phosphorus Uptake, potassium Uptake, nitrogen Dose and preceding PlantCorrection. These are showcased in Fig. 1.

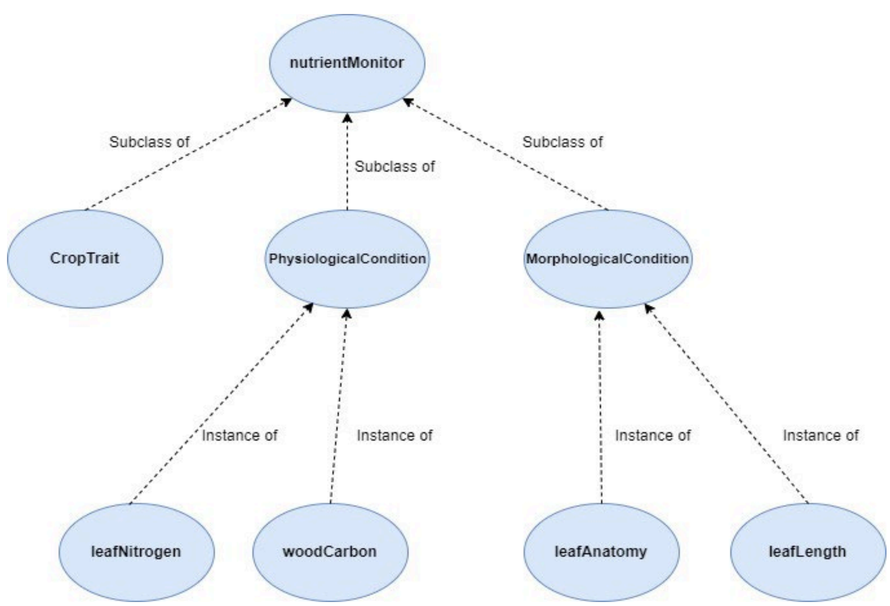

Fig. 1. Visualization of part of the pilot specific nutrient Monitor ontology.

[3] https://www.fao.org/agrovoc/

AIM is not a separate enabler. Instead, each enabler used in the system should use or create a *data wrapper* (essentially, a new enabler) that translates its native model to and from AIM, if it does not natively support AIM of course. Therefore, several such enablers (data wrappers) have been created that translate data obtained from the sensors to AIM and these can then be decoded by the data analytics and decision support enablers. For example, the data obtained through the Ex Machina dashboard (whose visualization is presented in Fig. 2)—more specifically, its corresponding RESTful API—are translated to AIM using a wrapper that was developed for this pilot.

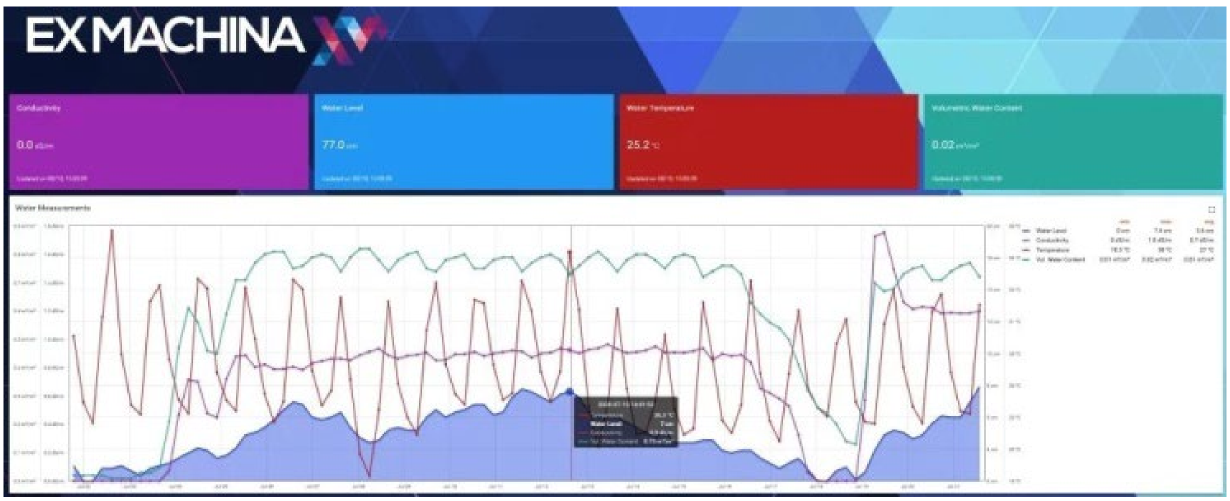

Fig. 2. Visualization of the measurements taken by sensors as displayed and relayed though the Ex Machina dashboard

Below we provide two brief examples using AIM in the context of pilot 1.3:

- Farm data example:

```
{
    "@context": [
         "https://w3id.org/demeter/agri-context.jsonld",
    ],
    "@id":"http://w3id.org/demeter/plot/1",
    "@type": "Plot",
    "hasGeometry": "Polygon((40.619107 22.822914, 40.617334 22.832324, 40.608583 
22.832286, 40.608607 22.825262, 40.619107 22.822914))",
    "identifier": "ELGO Kalochori Experimental station",
    "area": "1",
    "cropSpecies": {"@id": "http://w3id.org/demeter/CropType/6",
                    "@type": "CropType",
                    "name": "Rice",
                    "family": " Poaceae",
                    "description": " Oryza sativa, commonly known as Asian rice, 
is the plant species most commonly referred to in English as rice.",
                    "species": "Oryza Sativa",
```

```
                    "agroVocConcept": http://aims.fao.org/aos/agrovoc/c_5438
                    "production": {
                                productionAmount: "230 tonnes"
                     }
            }
}
```


- Meteo data example:


```
{
    "@context": [
         "https://w3id.org/demeter/agri-context.jsonld",
    ],
    "@id":"http://w3id.org/demeter/measurement/5",
    "@type": "Measurement",
    "hasValue": "28.3",
    "isMeasureIn":<http://www.ontology-of-units-of-measure.org/resource/om-2/
degreeCelsius>,
    "relatesToProperty": <https://w3id.org/def/saref4agri#AirTemperature>,
    "measurementMadeBy": {"@id": "http://w3id.org/demeter/station/gr/2",
                    "@type": "WeatherStation",
                    "name": "ELGO Kalochori Ex Machine sensor",
                    "hasGeometry": "Point((40.617544 22.831559)"
            }
}
```


Enablers Developed and Technologies Used

- **Optimal Fertilizer Usage Enabler**
  Nitrogen (N) is a fundamental ingredient in the fertilizers industry, either by itself or in mixtures. Its extensive use constitutes a leading factor in the global N cycle transformation and leaves an important environmental footprint, causing water eutrophication, ozone layer depletion and global warming. N is a necessary input in treatments and affects both the quality and quantity of yield in lowland rice grain and most other arable crops. Nevertheless, excessive amounts of applied N are not absorbed by the crop and burden the ecosystem via volatilization and denitrification. The N_2O compound possesses one of the highest global warming factors and accounts for the contribution of agricultural soil emissions to the greenhouse effect. N_2O is emitted heavily from chemical fertilizers, whereas N leaks to the soil as residue from the plant or excess non-absorbed nutrient.
  These facts suggest that N and its compounds should be limited and applied in an optimal manner. Modern agriculture should promote a better and more sustainable future. Precision farming promises solutions that lean towards this transition. In our case, this translates to an AI-aided decision support

system that estimates N content and recommends the optimal intervention in spatial, temporal, and quantitative manner.

This enabler receives a series of vegetation indices for arable crops as input and outputs a level-wise estimation on the nitrogen level—more specifically, N update (NU)—of different zones within the field. The indices are extracted by processing UAV and satellite imagery taken from the pilot. The regression models are trained using samples, which correlate the values of spectral indices derived from UAV imagery (inputs) with NU obtained from laboratory analysis of field samples (output), as derived from two small-scale field experiments that have been conducted on the pilot's site by ELGO. The Optimal Fertilizer Usage enabler implements an ensemble model that encapsulates both state-of-the-art and traditional classification algorithms, combined via a voting system to ultimately estimate the level of NU for every zone within a field plot. The module can be configured for any number of NU quantification levels, but the most common and accurate one is a distinction into three levels of NU status, following a "traffic light" labelling.

This enabler is developed as part of a bigger decision support system that provides the farmer with insights over the N treatment, in terms of both scheduling and the proper dosage. In general, UAV imagery is used for the small-scale experiments (i.e., for training the NU estimation models), but satellite imagery is used as input for real-sized fields. Sentinel-2 or commercial satellite imagery of even higher spatial resolution is preferred for this purpose, depending on the agricultural field's size and required detail (although UAV-collected images can also be used if available). Additionally, this module is developed in a way that allows scalability and generalization in other crops. Nonetheless, the enabler acts as a hidden layer of the decision support system.

The algorithm has achieved competitive results concerning accuracy and recall. Ground truth data from previous growing seasons were also used. The assessments indicate that the enabler's recommendations assist in designing an optimized, targeted intervention policy, mitigating the plant losses by at least 30% and the fertilizers' usage by over 10%. Moreover, selective treatment strengthens the soil and facilitates yield improvement. Equally important, these results impact the universal goal of a green and sustainable future.

It should be noted that the enabler also supports building the regression models with N concentration (NC) as output. This has been foreseen for increasing its reuse potential, since NC (instead of NU) is employed by several other empirical fertilization recommendation models proposed in the literature.

Fig 3: Visualization of the Optimal Fertilizer Usage enabler

- **Optimal Water Quality Enabler**
  Soil salinity is the procedure of mixing the soil with dissolvable salts, which results in leaving the soil saline. That is a severe problem in agriculture, since salinity decreases the productivity and the value of land. On the one hand, saline soils can result from irrigation, when using irrigation water that contain medium to high amounts of solvable salts, which accumulate over time. On the other hand, saline soils can also be the result of increased water use in coastal areas, because the sea intrudes the water table and seawater floods nearby fields during storms in the Mediterranean area. Rice is the main crop in wet areas such as river deltas in the Euro-Mediterranean region, typically as a continuous flooding cultivation. But because salinity is endemic in coastal areas, rice paddies are continuously irrigated with river water to reduce water salinity, thus wasting enormous volumes of irrigation water and considerable energy to pump water.
  A direct solution is to continuously monitor salinity via an appropriate IoT sensor (e.g., the WISyNode) and refresh the water whenever it is only absolutely necessary. But installing a sensor in each rice paddy is both expensive and can obstruct machinery operations. To this end, the enabler tries to identify salt toxicity stress of rice paddies without an in-situ sensor, indirectly via remote sensing imagery. The basic idea is that if the plants in a rice paddy with a WISyNode deployed in it are stressed due to salt toxicity (which is quantified by the sensor), then any detected stress in nearby paddies can also be attributed to increased salinity with high probability. Effectively,

the latter can be detected through a remotely sensed imagery and proper modelling, without requiring a WISyNode to be installed in each paddy.
Fig. 4 presents an example of the interface. First, the user loads a remote sensing image file (UAV-collected RGB image in this example) with the rice fields (small-scale plots in this example), selecting the time range to read data from (historic records of WISyNode readings) and the period the image was acquired. Next, the user should identify which WISyNode sensors should be used as reference for the rest of the paddies, via the choice "Calculate nodes range". Lastly, the user selects "Enable automatic Ex Machina reading salinity" to start gathering the WISyNode salinity measurements and the enabler outputs an estimate of the salinity for each image pixel. The latter is achieved via regression modelling, correlating multiband image vectors with the salinity measurements of the refence paddy.

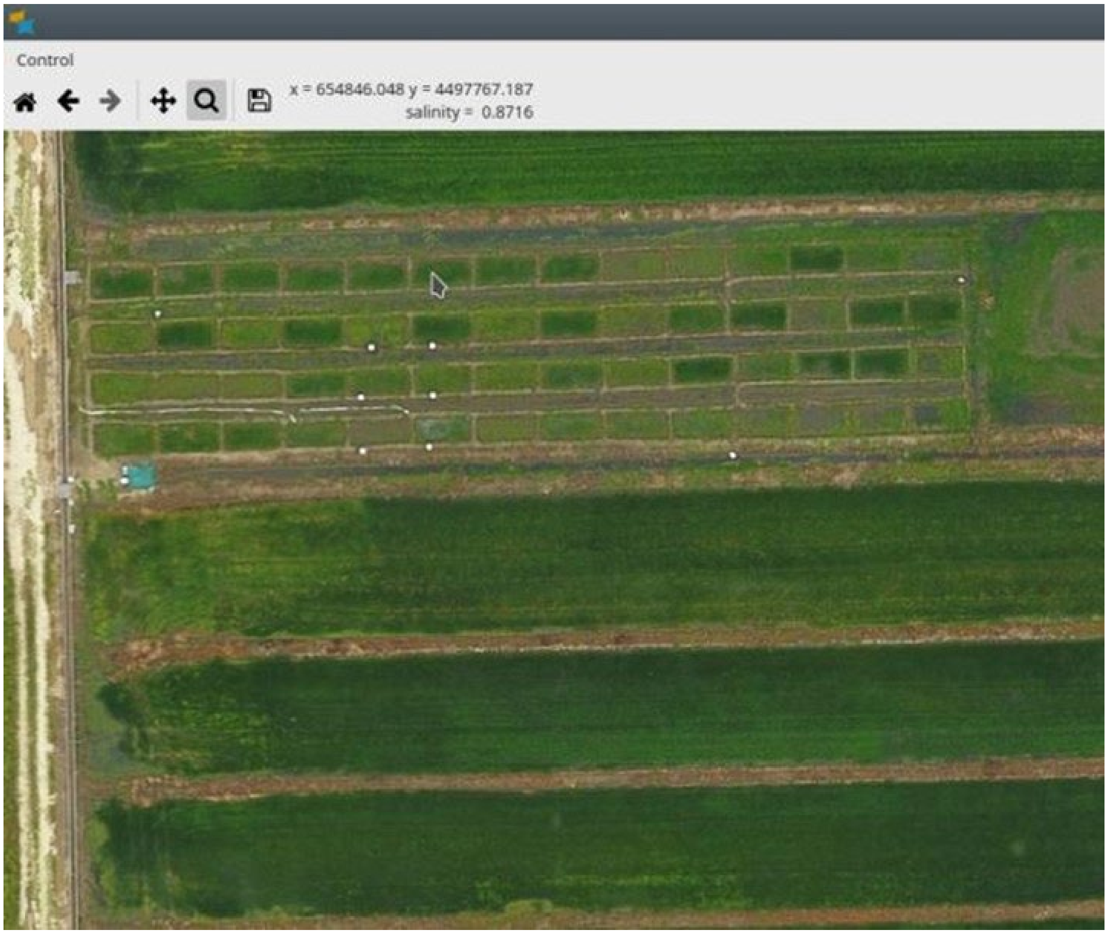

Fig. 4. Electrical conductivity values along with real earth coordinates.

Using this estimate of the salinity measurement it is then possible to make a decision regarding when to drain and rinse the rice paddies, even for areas not covered by WISyNode sensors, in order to both avoid crop yield loss (due to high salinity) and also to reduce the usage of water resources. This is done by the DSS enabler presented later in this document, who takes input from this enabler.

- Maize Irrigation (Analytics) Enabler
  The optimal irrigation management of maize crops is tightly linked to weather conditions. To this end, the Maize Irrigation Enabler provides localized forecasts of weather parameters, exploiting state-of-the-art regression modelling techniques. More specifically, the current enabler employs a Long Short-Term Memory Recurrent Neural Network (RNN-LSTM). The RNN comprises two inputs, one related to the present and one related to the past. The output of each step is fed as input to the next step via a feedback loop. The RNN maintains an internal state that is responsible for processing the data sequence in the input, which is used in a recursive rationale so that it can handle new data. The major problem of this RNN formulation is that it cannot handle the gradient problem and—as a result—it cannot effectively capture dependencies over an extended time history. The latter occurs because the RNN's training algorithm is eventually dominated by the most recent information. The solution to the problem is given by the LSTM architecture, which uses memory unit instead of RNN neurons. LSTM can support fast training and learn adequately via the use of continuous short-term memory, so that it can handle and store a large number of timeseries steps.
  To this end, we have implemented an application in the Python programming language, whereby we collect all sensor (in-situ and/or nearby meteorological stations) measurements linked to the area of interest. An RNN-LSTM models has been built for forecasting key weather parameters (i.e., temperature, wetness, and relative humidity) based on historical weather data (one model for each parameter). An example is showcased in Fig. 5. These forecasts are then used for supporting optimal irrigation management by providing input to the DSS enabler described below.
  It should be stressed that the data analytics provided by this enabler, essentially providing weather predictions that are then used for maize irrigation could be used in other applications as well, where such data might be necessary.

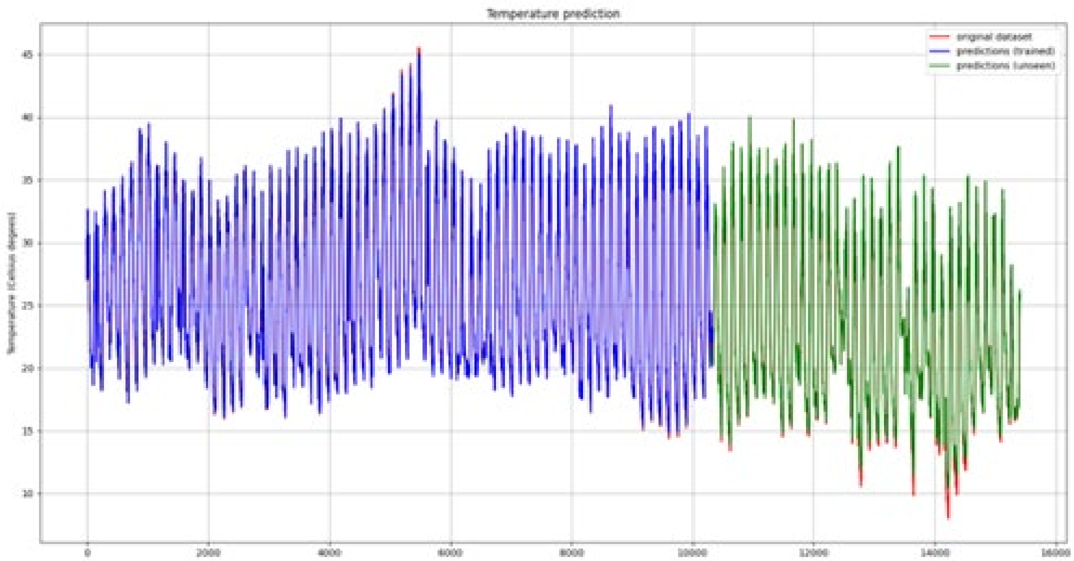

Fig. 5. Temperature forecasts obtained by the RNN-LSTM model. The reference dataset is depicted with a red, the predictions on the training set as shown with a blue line, whereas the green line presents the predictions on the unseen dataset.

- **Data Fusion Enabler**

  Throughout the pilot, there is a need to fuse data pertaining to the same (or similar) measurements that come from multiple sensors. In this way, it is possible to deal with partially inconsistent or missing data due to errors in one of the used sensors.

  To this end, we have developed an enabler that fuses (numerical) data describing the same type of information. Currently, this fusion is primarily performed on the weather data, but could also be applied to other types of data such as the water sensor data. In this pilot, weather information is provided by the following sources:

  a) privately-owned weather stations of ELGO,

  b) Ex Machina in-situ weather stations, and

  c) from local (nearby) weather services.

  The information from all three sources is fused to increase the accuracy and quality of the obtained data. The fused data is then fed as input into the data analytics and decision support enablers where they will be transformed into actionable data.

  The techniques used for this fusion process are based on statistical methods and on data similarity. More specifically, to deal with missing and potentially inconsistent data, it is necessary to impute the missing data using the assumption that “the relations within the missing parts are similar to those in the observed parts”. The approaches we explored, are first “generic hot deck imputation", which fuses data based on the similarity of the two data series and distances of data attributes, so as to replace missing data based on similar candidates, and, second, "predictive mean matching" which enhances the previous method by generating new data points, i.e., making predictions on the current dataset. The enabler primarily uses the first approach, however we are exploring the applicability of the second approach, modified by a number of other statistical techniques in order to improve the results of the fusion process as provided by this enabler.

- **Remote Sensing Image Processing Enabler**
  This enabler deals with the processing of remote sensed imagery, typically collected from UAV or satellite platforms. It serves as an auxiliary internal module that handles all image pre-processing steps, such as conversion of DN to reflectance values, reprojection when necessary, cloud screening, etc. Currently, out of the box support is provided for well-known multispectral sensors for UAVs (namely, Parrot Sequoia and MicaSense RedEdge-MX), as well as for both PlanetScope and Sentinel-2 satellite imagery (both assumed to be surface reflectance products). Nevertheless, it is a generic module that can handle any multispectral image, if the user provides the mapping of image bands to a predefined set of spectral bands.
  Apart from pre-processing procedures, this enabler also calculates the spectral indices needed from several other enablers. Many well-known such indices are supported. Finally, the enabler can also perform zoning of an agricultural field, i.e., splitting a single field into zones that require different N dosage, based on their growth status. This is achieved via an empirical clustering-based algorithm, segmenting an appropriate spectral index and employing empirical rules for identifying the existence or not of significant variations in the plants' growth within the field.

- **Irrigation (SIS-Rice and SIS-Maize) Enablers**
  SIS-Rice and SIS-Maize are the two decision support enablers (SIS being an acronym for Smart Irrigation Service), which provide irrigation recommendations to the farmers combining the information provided by several of the abovementioned enablers.
  Now, the rice paddies are constantly flooded during the cultivation period. Thus, the concept of irrigation in rice is completely different compared to all other cultivations (i.e., irrigated the crops such as maize). Managing irrigation in rice means maintaining the level of water at an optimal value, which according to the Best Practice Guides should remain approximately at 10 cm during the biological circle of rice to compete with the emerging weeds.

Moreover, the water should be renewed frequently to remain fresh (and thus avoid anaerobic conditions) and when the electric conductivity is high, salts should be washed out to the drainage channels via flooding to avoid yield losses.

Both water height and salinity levels (derived from water conductivity) are measured in real-time via the WISyNode sensor, which is deployed within the rice paddy and transmits data via the GSM network to a dedicated web platform. The measurements are retrieved via this external web platform's API, and transformed into an AIM-compliant format, in order to be consumed by the SIS-Rice enabler. The decision for nearby paddies without a WISyNode deployed within them is taken using the optimal water quality enabler instead. The service employs empirical rules of when to drain the flooded field (increased salinity or excessive water height) or when to further flood the field (insufficient water height). Meteorological conditions and forecasts are considered for fine-tuning the decision and providing an alert of when fields need to be drained and reflooded. This improves upon the current practice of draining the field often (to avoid yield loss), thus conserving water usage.

The SIS-Maize enabler follows a more traditional irrigation decision support approach, primarily based on weather forecasts and a set of empirical rules. When available, UAV-collected thermal imagery can be fused with the weather forecast information, although this is currently an experimental approach undergoing heavy testing. It should be noted that maize cultivation is interconnected with the rice one, since it is used in the rice crop rotation systems.

- **Fertilization DSS Enabler (FertiRM)**

  Nutrient monitoring and avoiding its overuse are common problems in agriculture, considering that over-fertilization can greatly increase cultivation costs and—perhaps most importantly—it increases the environmental footprint of the cultivation due to nitrates escape.

  The FertiRM service provides spatially variable nitrogen fertilization recommendations for surface fertilizations in rice and maize. The goal is to identify (through mapping) the field areas with lower vegetation and vigor as assistance to farmers, most of whom nowadays apply fertilizers using variable rate technologies. This facilitates the triptych of fertilization: when, where, and how much.

  The service is primarily based on the NU estimations provided by the Optimal Fertilizer Usage Enabler. These are translated to fertilizer dosage recommendation, based on empirical rules. As mentioned previously, NC estimations can be used instead, if the empirical recommendation model is based on NC. Weather forecasts are also used auxiliary, to fine-tune the decision (i.e., slightly adapt the date of application if heavy precipitation is anticipated). The recommendations are provided as spatial vector files (after the zoning procedure previously), which can then be fed to Variable Rate Technology (VRT) machinery. Along with the latter, spectral indices and NU/NC estimates (after an assignment into vegetation vigor classes) are also provided to the user via appropriate visualizations, in order to explain the system's decisions and thus gain the farmers' trust.

Integration Into Pilot Applications

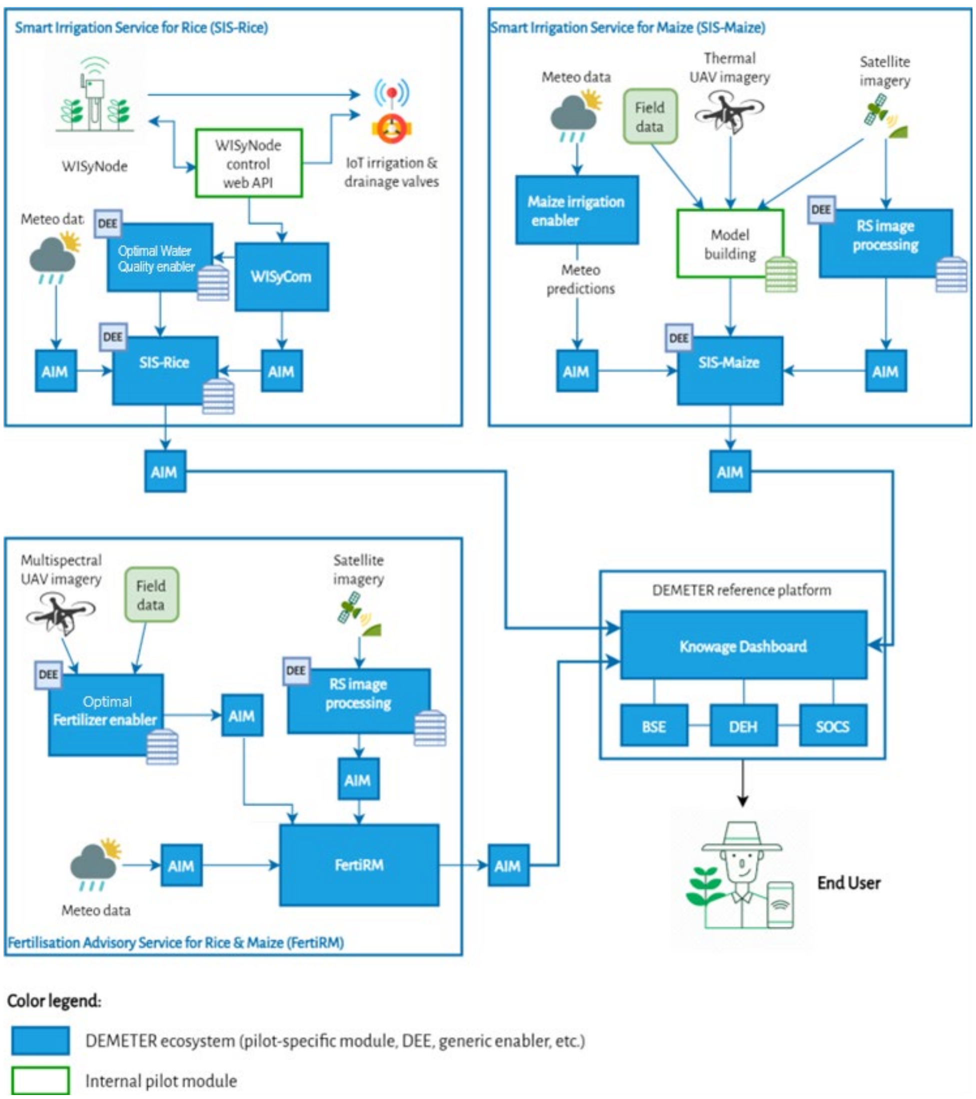

Fig. 6. The DEMETER architecture and developed components as applied to the use-case and its three applications.

The enablers we just presented have been integrated into three specific applications which are presented in Fig. 6:

- *Smart Irrigation Service for Rice (SIS-Rice)*: this app's goal is to drain the rice fields when salinity increases and to flood them with new clean water, while decreasing overall water usage.
- *Smart Irrigation Service for Maize (SIS-Maize)*: the goal is to water only when needed, decreasing total water usage.
- *Fertilization Advisory Service for Rice and Maize (FertiRM)*: the goal is the total net reduction of cost for fertilizers per unit of yield obtained, estimating the appropriate dosage for each management zone zones within the field.

The enablers are registered and discoverable via the DEMETER Enabler Hub (DEH), and using the DEMETER architecture and integration tools, the final apps can be instantiated. The initial deployment of these DEMETER apps has taken place in the ELGO stations at the Kalochori and Thermi areas (Central Macedonia, Greece) and was conducted starting from summer 2020, in order to test the equipment used, the software for interfacing with these sensors, and the integration of the various enablers into the apps and with the core DEMETER enablers. Then these apps were deployed to several independent farmers who are collaborating with the pilot and provide their fields during the 2022 planting period.

5 Feedback from farmers

DEMETER follows a Multi-actor Approach (MAA) in order to have the farmers at the centre of the app development process, and to take their needs as a key input in developing a solution suitable for these needs. Engaging the farmers and getting feedback from them has been conducted (either directly or via surveys) in several presentations and workshops that were organized by ELGO between 2019 and 2022. About 20 farmers participated in each one of these. In the initial workshops, the farmers' needs were identified, then the solutions developed were presented and in the most recent ones, the system and how to install the automatic rice irrigation and the drainage system and sensors was showcased.

Remember that the whole system has been developed with two main deployments conducted: the initial deployment of the system during the growing periods on 2020 and 2021, was meant to test the system and receive further feedback from the farmers, which was in turn integrated into the three apps. Then, the second phase of deployment in 2022, provided the updated system for further testing and final feedback from the end users, before finalizing the work on this pilot. ELGO has plans to keep offering the system on a subscription basis afterall, so there is a strong incentive to integrate any feedback that might make the system more marketable.

6 Benefits

The three apps provide data analytics and decision support to the farmers in order to maintain their yields while reducing the usage of resources (water and fertilizer), which is also good for the environment and society in general. This is measured by the following KPIs, which capture the improvements provided by utilizing the developed apps compared to previous recorded usage:

- **Decrease of fertilizer usage**, measured in usage per ton of yield, by 15% compared to the documented average of conventionally treated fields.
- **Decrease in irrigation water consumption**, by 10-15% compared to current measured usage (documented in previous studies).
- **Monitoring salinity (electrical conductivity) and water height in rice paddies**: conductivity has to be regulated below the critical threshold of **3 dS/m**, so that yield is not affected negatively. Combined with water height level monitoring, this greatly conserves irrigation water in rice paddies and decrease the farmers' visits, thus reducing labor hours and—most importantly—the carbon footprint of the rice cultivation.

Regarding, the benefits for the technical partners, ELGO has expanded its range of technologies and improved the solutions offered to farmers, whereas ICCS had the chance to apply AI and data technologies to the agricultural domain and obtain significant experience in the deployment of such technologies to the pilot.

7 Conclusions

This white paper presented the work conducted for pilot 1.3, aiming to improve rice and maize yields, while reducing the resources (water and fertilizer) used. Using digital agriculture and IT technologies, a reduction in the consumption of resources (water and fertilizer by about 15%) was achieved while maintaining the salinity of the water used to irrigate the rice below a critical threshold (under 3 dS/m), which also ensured that the yield remains optimal despite the reduced usage of resources.

Several new enablers have been developed and then these have been integrated using the DEMETER architecture and key enablers in order to provide three decision support apps. These apps were then provided to end users (farmers) and deployed on their fields as well as the ELGO experimental field. Farmers were educated in the usage of these apps and enablers and ELGO is examining a business model to provide these services to farmers on a subscription fee basis.

CONTACT US

Kevin Doolin, Project Coordinator

Kevin.Doolin@WaltonInstitute.ie

or email **INFO@H2020-DEMETER.EU**

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