# Intelligent Pesticide and Irrigation Management in Precision Agriculture: The Case of VELOS Project

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**Abstract**
Precision agriculture is a new and evolving discipline that uses advanced technologies to increase the efficiency of agricultural inputs in a profitable and environmentally friendly way. Emerging techniques, such as Internet of Things, Artificial Intelligence, Big Data analytics, and Unmanned Aerial/Ground Vehicles can be utilized in order to make informed management decisions aiming to increase crop production. In this paper, we present the architecture of VELOS, a smart ecosystem for pest management and irrigation of bean farms in the Greece Region Prespa. VELOS leverages the aforementioned techniques for extracting knowledge in order to create integrated solutions to effectively support decision-making for efficiently managing pesticides and irrigation applications and scheduling.

**Keywords**
Precision Agriculture, Internet of Things, Artificial Intelligence, Unmanned Aerial/Ground Vehicles, Pesticide and Irrigation Management

## 1. Introduction

The integration of novel information and communication technologies (ICT) in the primary production sector enables data collection and analysis concerning critical parameters of the production process, while predictive mechanisms exploiting Artificial Intelligence (AI) and Machine Learning (ML) techniques, lead to the generation of new knowledge and support informed decision making, contributing to production quality and increased quantity, profit maximization, cost reduction, and overall environmental footprint minimization. In the precision agriculture domain, minimizing pesticide usage and irrigation application has profound positive effects to **a) crop yield** (optimizing its quality and quantity), **b) farmers** (minimizing production costs and increasing yield), and **c) environment** (minimizing agricultural footprint to natural resources, i.e., degradation / depletion of natural water resources and pollution).

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*VELOS* is a smart ecosystem for pest management and irrigation of bean farms in the Prespa Region. The ecosystem leverages on Internet of Things (IoT) technologies, Unmanned Aerial and Ground Vehicles (UAVs/UGVs), Low-Power Wide-Area Networks (LPWANs), AI, and ML techniques for extracting knowledge in order to create integrated solutions to effectively support decision-making for efficiently managing pesticide usage and irrigation scheduling. *VELOS* consists of: **a) wireless sensors** for real-time data collection and an easy-to-install and configurable LPWAN, **b)** automated **UAV fleet management system**, following the UAV model-as-a-service, **c) UGV** with robotic mechanisms, and **d) data platform**, which correlates and analyzes IoT data, open data and data retrieved from existing systems and applications, **e) prediction / classification models and thresholds and risk indicators** that allow risk assessment of pests / diseases' appearance in bean farming, **f) smart decision-making system** for the application of pesticides and irrigation, and **g) traceability system** for the final product. The proposed system will be deployed, and its performance will be verified in four pilot fields in the Prespa Region.

The rest of the paper is structured as follows. In Section 2 we present the proposed architecture of *VELOS* and discuss on the individual subsystems, while in Section 3 the current pilot setup is briefly described. Finally, in Section 4 concluding remarks are made and future work is highlighted.

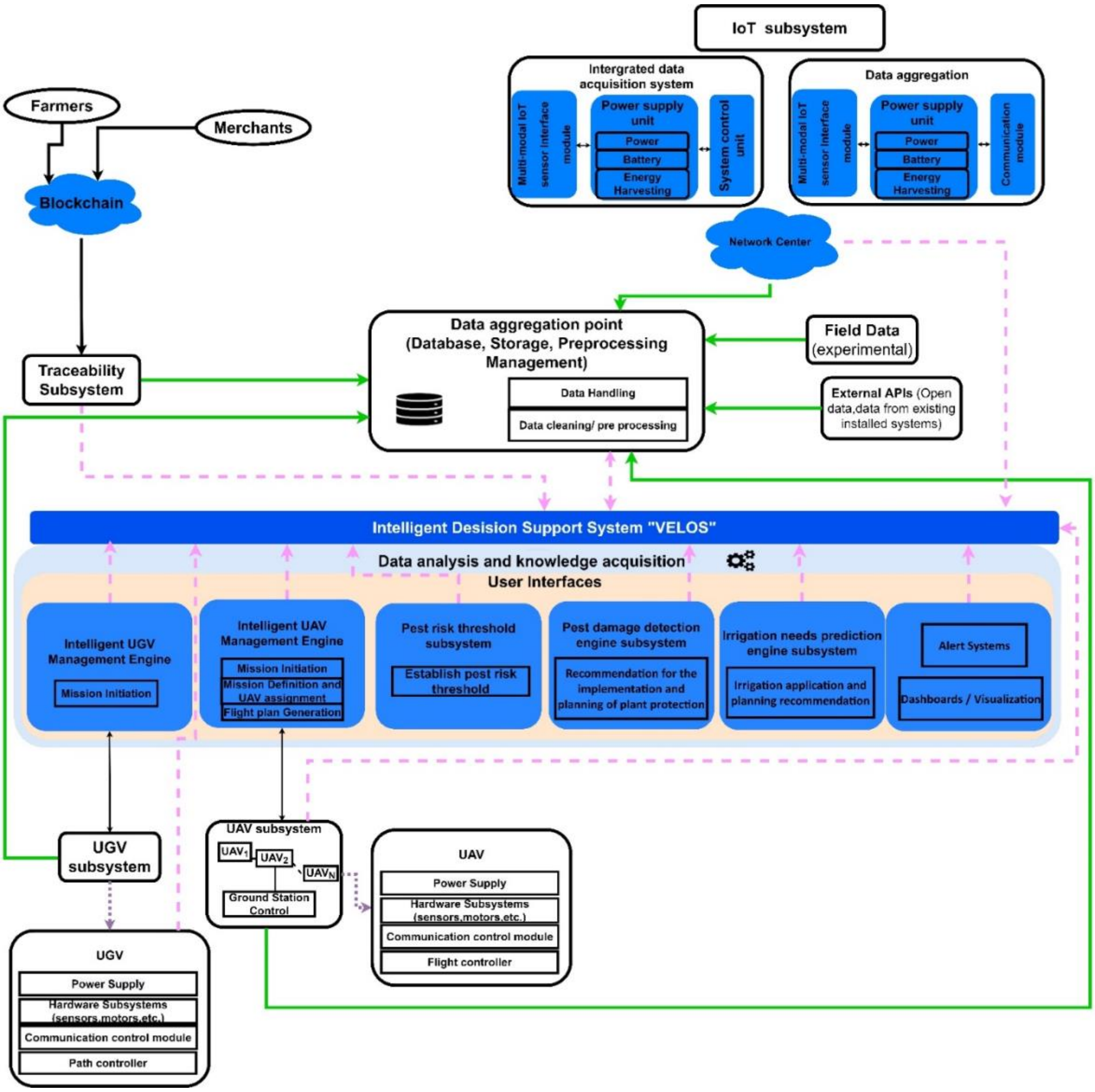


**Figure 1**: The architecture of VELOS

## 2. The Case of VELOS

The proposed architecture of VELOS project, depicted in Figure 1, includes several subsystems, that closely interwork aiming to assess the risk of occurrence and predicting bean infestations by arthropod pests and plant diseases, as well as making scheduling recommendations for pesticide usage and irrigation application to protect crops and optimize their yield. VELOS is an open-source, modular, and scalable framework, adding, exchanging, modifying, and upgrading software components / subsystems in an easy manner, ensuring interoperability between applications and subsystems. The system follows the design of N-level architecture, in order to be flexible, robust, efficient, providing also workload balancing to system units and workstations.

### 2.1. IoT Subsystem

A Long Range Wide Area Network (LoRaWAN) [1] is considered the best option for the transmission of IoT related collected data (e.g., soil moisture, temperature, humidity level) in the VELOS ecosystem, due to the flexible scalability, low network development cost and prolonged lifetime of end devices. The VELOS ecosystem will effectively exploit a telemetric meteorological station network already installed in the Prespes area.

### 2.2. UAV Subsystem

The proposed UAV subsystem includes UAV fleet management capabilities, following the concept of UAV-as-a-service model [2], in order to address identified impediments in the agriculture sector (e.g., expensive equipment, enhanced skills and training that farmers are usually unwilling to receive [3]) and bring UAVs full potential to precision agriculture. This model supports the organization and coordination of available UAVs to achieve common goals. The UAV fleet will include UAVs belonging to one or more providers, supporting their management and coordination in order to collectively process and satisfy crop monitoring requirements in agricultural production, considering also UAVs already involved in a mission in the area of interest. The UAV subsystem includes mission initiation and definition, UAVs assignment, flight generation, and the ground control system.

### 2.3. UGV Subsystem

VELOS exploits a custom-made robotic UGV that will be constructed to enhance collected data quality and improve pest prediction accuracy. The VELOS UGV necessitates a solid construction that will be equipped with DC motors, enabling movement in the area of interest, a robotic arm mounted with a spectral camera, sensors for obstacle avoidance and GPS receivers. Other requirements and constraints imposed, i.e., bean cultivation specific growing parameters and practices will also be taken into account. A central microprocessor will provide the best path to the area of interest according to an optimal path finding algorithm, considering different parameters, such as energy consumption and/or time necessitated for completing the specific mission.

### 2.4. Pest Risk Threshold Subsystem

Empirical prognostic degree-day thresholds and epidemiological plant disease risk indices will be developed, in order to timely forecast the seasonal occurrence of the most important arthropod pests and diseases of bean cultivation. Particularly, degree-day thresholds for *Helicoverpa armigera*, *Thrips sp.* and *Tetranychus urticae* will be developed and further validated, as well as epidemiological growth risk indices for the fungal pathogen *Uromyces phaseoli* which is the cause of bean rust. The development of pest degree-day thresholds and plant disease risk indicators uses a combination of methodologies and techniques based on the analysis of meteorological data and field observations of the phenology and/or damage caused from the aforementioned pests [4]. Data from two growing seasons (2021 and 2022) are collected and used along with demographic parameters and temperature-dependent developmental thresholds available from published research. At the functional level, the pest risk threshold subsystem inputs real-time weather data to generate pest risk alerts and relevant information about management actions to control pests.

## 2.5. Pest Damage Detection Engine Subsystem

The pest damage detection engine (PDDE) subsystem aims to detect arthropod pest damage and/or plant disease symptoms based on images taken by UAVs and UGVs. ML algorithms have been used extensively for pest damage and disease recognition in plants [5]–[11]. The input is typically a set of images, and a ML algorithm is applied to categorize the depicted plant either as healthy or not, and in the latter case, determine the disease. The PDDE subsystem applies a portfolio of detection models to get the best possible result. Specifically, it utilizes several state-of-the-art models based on convolutional neural networks (CNNs). These models are region-based detectors like Faster-RCNN [12] and single-stage detectors like SSD [13], RetinaNet [14], EfficientDet [15], YOLOv4 [16], and YOLOv5 [17]. The PDDE subsystem, also, applies several preprocessing techniques such as image resize, data augmentation, and image denoise to increase the accuracy of the models. To date, the UAV and UGV based PDDE subsystem will be able to work adjunctively in conjunction with the pest risk thresholds subsystem and activated only during the periods of high pest risk attack to give estimates of the size and extent of actual infestation during periods of favorable conditions for disease epidemics rather than to be used as a diagnostic tool *per se*.

## 2.6. Irrigation Forecasting Engine Subsystem

The irrigation forecasting engine subsystem predicts the irrigation needs of a field. The problem of predicting irrigation needs is approached as a regression one. We utilize a portfolio of various ML regression algorithms, e.g., support vector machines, decision trees, random forest, multi-layer perceptron regressor, to generate regression models and select the most accurate. Also, we use a plethora of preprocessing techniques, to reshape and modify data, so that non-existent measurements / values at predetermined intervals or outliers in the measurements received are recognized in a timely manner, and do not lead to erroneous conclusions.

## 2.7. VELOS Intelligent Decision-Making System

The VELOS Intelligent Decision-Making System (DSS) is the heart of the system, orchestrating the rest of the subsystems in order to generate informed recommendations on pesticide application and irrigation management. Regarding pesticide application, the proposed system includes a three-stage approach of pest prediction, which is expected to improve the system's overall prediction accuracy (graphically illustrated in **Figure 2**). Degree day thresholds and disease risk indices will be complemented with UAV flight missions (either pre-scheduled or triggered by user requests and/or DSS due to approaching specific indicators favoring the development of considered diseases). In case of scheduled or user-triggered UAV missions, PDDE predictions are reconsidered and further enhanced taking into account IoT data and pest risk thresholds defined. As a next step, UGV subsystem is activated, provided with corresponding coordinates to obtain more images of the afflicted area, which are given as input to the PDDE subsystem, and feed the models with new data that improve their predictions.

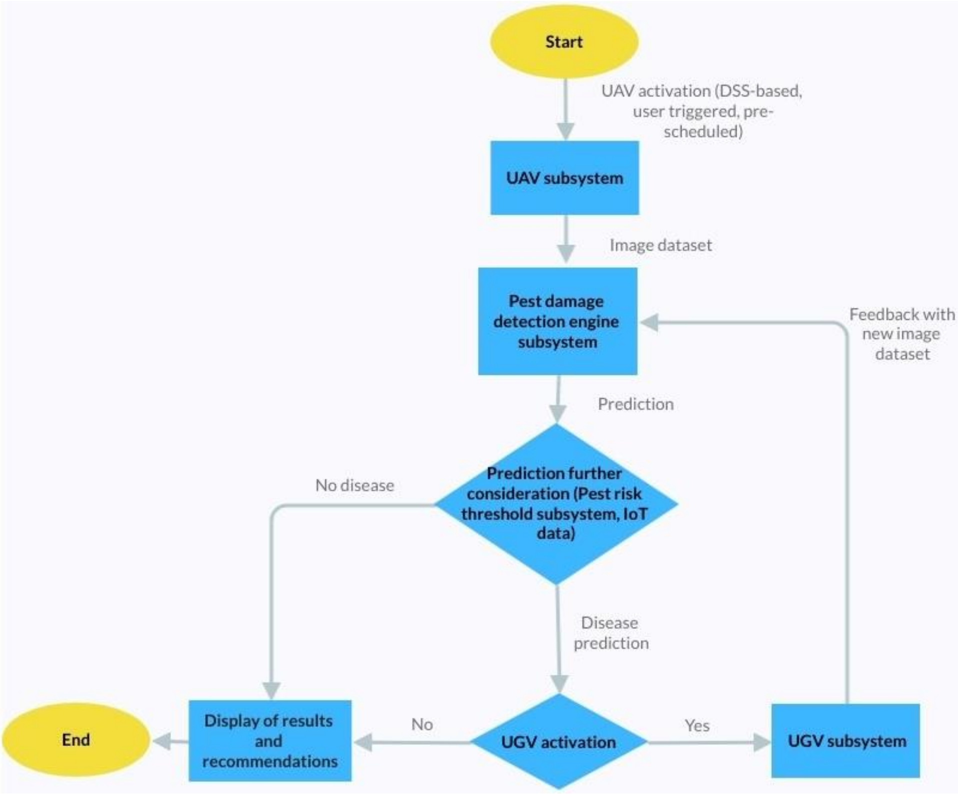


**Figure 2**: Pest detection and prediction flow chart

Finally, VELOS DSS makes an appropriate plant protection recommendation to farmers based on the identified disease. Coupling UAVs, UGVs image analysis and PDDE-based predictions with thresholds and risk indices developed for the bean cultivation, we can minimize the false-positive predictions of the applied ML algorithms.

The irrigation forecasting engine subsystem collects IoT related data (e.g., soil moisture, temperature, rainfall) and data from external subsystems (e.g., open meteorological data and weather forecasts), applies a portfolio of regression ML techniques and produces the final irrigation needs for the pilot fields. Finally, VELOS DSS suggests an appropriate irrigation schedule to farmers based on the identified needs. The irrigation needs forecasting flow chart is presented in **Figure 3**.

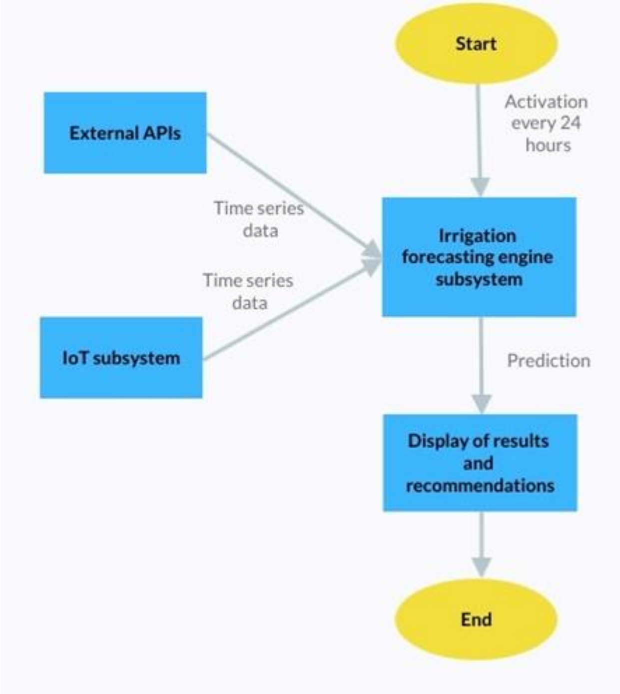


**Figure 3**: Irrigation needs forecast flow chart

## 3. Experimental Setup

At present, a telemetric meteorological network has been installed consisting of seven meteorological stations (as depicted in Figure 4) distributed in the main bean growing area of Greece and above the border area of the Prespa National Park. The network sends data remotely to a cloud-based server that uses the ADCON addVANTAGE software (as presented in **Figure 5**). A pilot experimental field network has been established since 2021, in order to obtain pest field data, necessary for the development and evaluation of pest threshold predictions. Pest specific monitoring and sampling protocols have been developed and implemented for the pilot field.

During each of the bean growing seasons, sequential observations are taken twice a week from four experimental bean plots (4-7 acres each). Two of the plots are conventional and two organics, the latter receiving no treatment with pesticides and serving as controls. Field data for 2021 consistently demonstrate the presence of *H. armigera*, *T. urticae*, and *U. phaseoli*, which in combination with meteorological data are the basis for the development of degree-day pest thresholds and bean rust indices, respectively. This allows the initial development of empirical thresholds and indicators for the above species for the year 2021. These thresholds will be evaluated during the current growing season for the year 2022. Degree-day pest thresholds and plant disease risk indicators are a profound empirical oriented mathematical approach for pest prediction and a prerequisite for the operation of the ongoing integrated software system for forecasting and decision-making for the plant protection of bean cultivation in the Prespa region. For 2022, UAV and UGV based images will be collected from the pilot fields so as to train the ML models of the PDDE subsystem, while additional soil moisture sensors will be installed in order to further support the irrigation forecasting engine subsystem.

**Figure 4**: Meteorological data collection stations from the study area

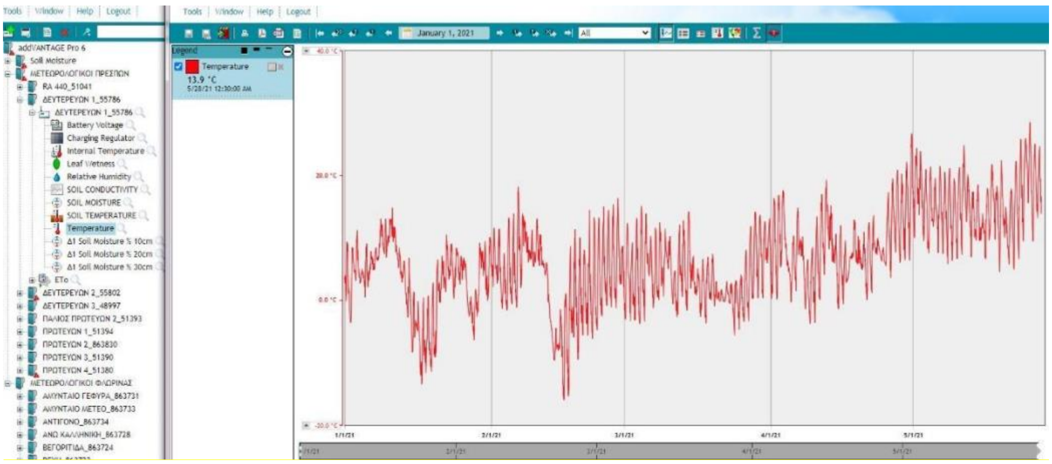

**Figure 5**: Real-time daily temperature recording at one of the meteorological stations located in the Prespa region

## 4. Conclusions

The VELOS project aims to assess the risk of occurrence and predict infestations of bean cultivation by arthropod pests and plant diseases, as well as making pesticide usage and irrigation application scheduling recommendations for plant protection and optimization. All subsystems of the VELOS system have been presented and the most important use cases of the Intelligent Decision-Making System have been graphically illustrated. In addition, the current experimental setup was briefly described. Field data for 2021 demonstrated the presence of *H. armigera*, *T. urticae*, and *U. phaseoli*, which in combination with meteorological data are the basis for the development of degree-day pest thresholds and bean rust indices, respectively.

Future work includes development of empirical thresholds and indicators for the above species and their evaluation during the current growing season for the year 2022. These pest thresholds will also be incorporated into the pest damage detection engine subsystem for improving prediction accuracy.

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