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# Rapid Plant Development Modelling System for Predictive Agriculture

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## Abstract

*Actual and upcoming climate changes will evidently have the largest impact on agriculture crops cultivation in terms of reduced harvest, increased costs, and necessary deviation from traditional farming. The aggravating factor for the successful applications of precision and predictive agriculture is the lack of big data due to slow, year-round cycles of crops, as a prerequisite for further analysis and modelling. The goal of our proposed system is to enable rapid collection of data with respect to various climate conditions, which are artificially created and permuted in the encapsulated design and correlated with plant development identifiers. The design is equipped with a large number of sensors and connected to the central database in a computer cloud, which enables the interconnection and coordination of multiple geographically distributed devices and related experiments. This accumulated data is exploited to develop mathematical models of wheat at different growth stages by applying the concepts of artificial intelligence and to utilize them to predict crop development and harvest. The paper focuses on a system concept to gather data for future models to be used publicly and interactively through a portal for predicting plant development under real and hypothetical climate conditions.*

***Keywords:*** *plant growth encapsulated design, rapid plant development modelling; IoT, big data, artificial intelligence, predictive agriculture.*

## 1. Introduction

Artificial intelligence (AI) today is significantly focused on increasing the efficiency of different sectors and reducing negative impacts on the environment. The agriculture sector started adopting the AI only recently, following the development of Internet of Things (IoT) as distributed networks of sensors and other devices [1] that enabled precision agriculture and the formation of large datasets [2]. The number of IoT devices in agriculture was projected to increase from 30 million in 2015 to 75 million in 2020 [3] and to offer significant precision farming opportunities such as: crop monitoring, disease detection, storage optimization, treatment optimization, irrigation and weeding [4, 5]. Successful examples of precision agriculture analytics include crop prediction by fruit counting or estimation from crop images with different spectra with 70-90% reliability of estimation accuracy [6], or modelling and forecasting of corn yield by neural networks depending on soil treatment [7]. A wider application of these methods is still in its infancy, as research began only a few years ago, mainly out of concern for climate change. The biggest aggravating factor for the successful application of AI is the lack of large amounts of data as a prerequisite for further analysis and modelling. Due to slow, year-round cycles, and the distinct specificity of individual locations (soil and weather conditions), it is not possible to promptly create a significant database of historical data. In addition, it is necessary to install a large number of sensors on different fields, which is one of the most propulsive areas of modern agriculture [8]. Moreover, climate changes are one of the most expressed aggravating factors for obtaining the relevant datasets.

The "big data" issue is addressed here by creating specially designed bioreactors that serve as rapid plant model identification systems of multiple simultaneous climate zones, supported by autonomous real-time data acquisition and archiving. Instead of the usual observed annual life cycles in nature, the system introduces equipment for rapid, simultaneous implementation of a number of different experiments in a climate-encapsulated system with control loops of light, temperature, humidity, pH and nutrient profiles, with an extensive network of sensors and with the help of multi-spectral cameras. The equipment is supported by software in the form of an autonomous storage of identifiers in a central database. For the exemplary case of the wheat, a single encapsulated design enables 8-12 simultaneous plant groups, each one as individual field emulation, capable of squeezing up to three yield cycles in a single year, resulting in total with 24-36 harvests per year per device that is the size of a computer server cabinet.

With a significant amount of historical data available, mathematical models of several different stages of wheat crop development are developed using AI (artificial neural networks, genetic algorithms) with respect to different, artificially created and permuted, microclimate conditions correlated with identified plant growth and development indicators at different stages.

The paper is a concise version of [11], organized as follows. Overall methodology of the approach is presented in Section 2. Encapsulated design and basic features are described in Section 3 while the architecture of the supporting IT system is described in Section 4. The AI plant development models are outlined in Section 5 and the conclusions are presented in Section 6.

## 2. Rapid plant modelling system methodology

The proposed methodology utilises the developed encapsulated design (apparatus) for accelerated experiments of plant growth in an isolated environment with autonomous permutation of artificial climatic conditions (light profile, temperature, humidity, airflow, pH and nutrient level) and archiving plant growth and development indicators collected by different sensors and multi-spectral cameras. The apparatus, i.e. the prototype of the system, implies constructional, assembly and electronic preconditions, and corresponding control loops to achieve the desired stated conditions in real-time and at the same time to regulate several different climatic conditions in an isolated environment.

The constructional prerequisite of the system ensures isolation from external conditions and enables a spatially compact design suitable for separating several different climatic conditions. The isolated environment also allows the simulation of conditions that are not yet present in the considered climates but are expected to occur under the influence of climate changes. The prerequisite includes a system for irrigation and nutrient supply through pumps and tubes to each individual plant, artificial LED lighting of different spectra and a heating and cooling system.

The electronic prerequisite includes electronic support, sensors, and control hardware for the regulation of the mentioned climatic conditions, as well as support for easy adjustment of parameters for future experiments. The implementation of experiments aims to be significantly accelerated by the simultaneous possibility of providing different conditions and the use of cameras and a mesh grid network of sensors with autonomous archiving of data in real time, which is then a suitable starting point for determining correlations between conditions and plant growth through advanced machine learning algorithms.

The proposed methodology aims at isolating plant physiognomy identifiers that are related to the faster or slower plant development at different stages. There are roughly one hundred phenological stages of wheat growth (BBCH scale) [9] and the system shares the data for three generalized ones: i) germination, ii) plant formation and maturation, iii) grain maturation, which are a general approximation for many plants, with the open possibility for the concept to be transferable to other species. Physiological identifiers such as stomatal transpiration, photosynthetic effect, night respiration, intercellular carbon dioxide concentration, evaporation, etc. are associated with physical and more accessible, i.e. measurable, identifiers such as water and nutrient absorption measured by multi-spectral camera, precise growth measurement, images in different spectra in certain modes (day and night), etc. Individual relevant parameters measurable by sensors and correlation with the growth and development of the plant are autonomously archived in real time together with the given climatic conditions in which the plant is located, gradually forming a very large database suitable for determining correlation relationships by advanced machine learning algorithms. Thus obtained, accurate data on isolated and artificially created climatic conditions and consequent plant development are autonomously archived and over time build a large data set of 6 million records collected in 5000 climate scenarios over a period of 2 years, which is suitable for applying algorithms in mathematical modelling and then predicting future plant developments in the coming climate change. The obtained mathematical models will be checked on a separate set of data and with the identification of the reliability of the estimate based on the forecasted conditions to give a prognostic illustration of the expected plant development. To increase the reliability of prediction, the models are classified and reduced to three parts depending on the plant stage: i) germination, ii) plant formation and maturation, iii) grain maturation.

The objectives of the system are as follows:

- develop the apparatus for rapid plant growth data collection, storage, and processing,
- conduct experiments in 5000 climate scenarios over a period of 2 years,
- obtain a relevant dataset of 6 mil. entries for the chosen wheat crop,
- apply machine learning algorithms for 3 different growth stages to obtain various use-case models of wheat crop development,
- structure the dataset and the models to be exploited for prediction of crop maturation, grain moisture and optimisation of pest treatments.

## 3. Encapsulated design plant growth devices

By being able to control the microclimate environment, the encapsulated design exploits the outdoor environment and further superposes desired artificial environment (temperature, soil humidity, air humidity, photosynthetic lighting, $CO_2$ and $O_2$ concentration and aeration) to experiment plant growth and development under different (sometimes extreme) microclimate conditions, collect and analyse the data to build artificial models that are further used for large scale harvesting predictions. The structure of the encapsulated design is shown in Fig. 1 with the upper part intended for plant growth and environment control and electronic support located within the enclosed drawer. It is important to note that within a single device it is possible to achieve four separate microclimatic zones with corresponding sensors and actuators in each zone. The considered devices are based on intelligent, self-sustainable home gardens of Urban Oasis Croatian manufacturer, which was additionally modified by the research team to enable a system for rapid modelling of plant development.


**Fig. 1.** Encapsulated design plant growth device [11].

The measured microclimate parameters are: i) air temperature, air flow, air humidity, photosynthetic photon flux density and soil moisture. Plant development indicators are the spectral image light intensity (3 bands), leaf area index (estimated), normalized difference vegetation index (NDVI), simple ratio (SR), photochemical reflectance index (PRI) and chlorophyll index (CI).

*Climate parameters regulation*

Air temperature: temperature control is achieved using temperature sensors, positive temperature coefficient (PTC) ceramic insulated heaters, ventilation system and the influence of the disturbances such as LED lights, solar irradiance through glass cabinet or electronic devices residual heating. The heating element is used in combination with fans to control the air flow.

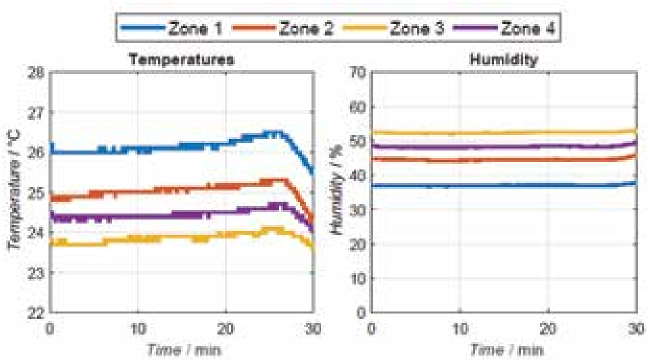
$CO_2$ concentration: by cabinet ventilation, the plants have access to the surrounding $CO_2$ concentration, and photosynthesized oxygen is removed from the encapsulated design. Increased $CO_2$ concentrations are achieved by putting the devices in a populated environment (faculty offices) where the concentration can reach up to 3000 ppm. There are two modes of operation: night (respiratory) and day (photosynthetic), both regulated with the inflow and outflow of the external air and $CO_2$ sensors in the individual zones and matching control loops with PI controlled fan speeds.

Lighting: for normal growth, the plants require approximately 500-1500 μmol/m$^2$/s of PPFD, which is the amount of PAR spectrum photons that reach the plant [10]. This correlates with required 200-500 W per m$^2$ of LED light power of the PAR spectrum, which is additionally increased to compensate the distance from the light source. Rather than having a multi-kilowatt lighting system, the sunlight is fully exploited by the glass structure of the encapsulated design, and artificial lighting is used to additionally increase the intensity, permute the outside conditions and extend the luminance duration. Artificial lighting is controlled by PI controller of the LED lighting intensity by PWM and a photosensor, individually in all four zones.

Soil moisture and air humidity: water is delivered to the soil by pumps and valves to each of the four zones individually and controlled by corresponding hysteresis controllers based on the information gathered from the electrical conductivity sensors placed in the soil. Valve on/off duration transforms the water flow in the tubes that supply water to the soil from within of the central tower. In the plant area of the encapsulated design, the humidity control loop consists of a humidity sensor, an ultrasonic humidifier and a corresponding fan that distributes the mist into the leaves. The setpoint of 0-100% humidity is achieved by a PI controlled fan speed.

Nutrients: the amount of required nutrient chemicals for plant growth has a significantly slower dynamics than other systems, with a measurable difference occurring after few months with real-time pH embedded sensors grade. Therefore, the soil is preconditioned prior to conducting the experiments in a laboratory environment and with highly accurate pH level sensors.

An exemplary established microclimate in the four zones of the device is shown in Fig. 2 as time-responses



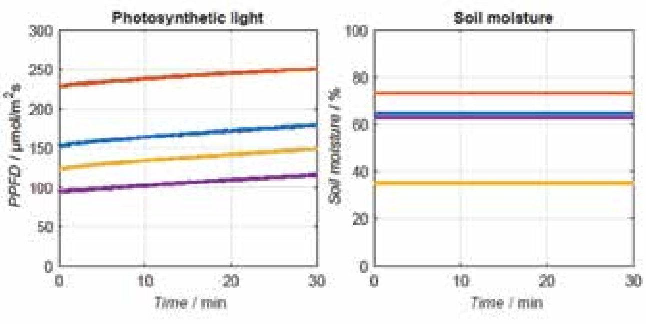



**Fig. 2.** Microclimate in 4 zones for an exemplary case study.

of temperature, humidity, light intensity, and soil moisture during a chosen period of 30 minutes.

*Measured identifiers*

Physiological identifiers such as stomatal transpiration, photosynthetic effect, night respiration, intercellular carbon dioxide concentration, evaporation, etc. are associated indirectly with physical and more accessible, measurable vegetation indices relying mostly on multi-spectral cameras as sensors. This is necessary to enable a large number of measurements, as accurate plant status identifiers from the domain of molecular biology are both time-consuming and costly, and may be associated with a correlation delay with respect to other input-output data. In order to capture both the spectral bands required for basic vegetation indices as well as additional bands to power further analytics, a multi-spectral sensor RedEdge-MX was chosen.

## 4. Software architecture

The architecture of the chamber's software support (depicted in Fig. 3) includes the established i) database on the central data server, ii) computer cloud architecture, directly connected with iii) sensors and actuators of the devices utilised to conduct experiments. The data from the sensors and actuators are collected every 15 minutes and stored in the cloud computer; from there they are retrieved once a day, stored in the central server database and made available for advanced analysis.

Device software layer: divided into multiple subsystems, namely the control and regulation subsystem, the network subsystem and multiple sensor subsystems. The embedded controller in the control and regulation subsystem is a real-time controller for ensuring desired environmental conditions within the devices, i.e. wired connectivity with the sensors and actuators, and real-time execution of the control loops. The architecture of the device's software, along with actuator and sensor control, implies the established communication with the computer cloud through which telemetry data and status reports are sent.

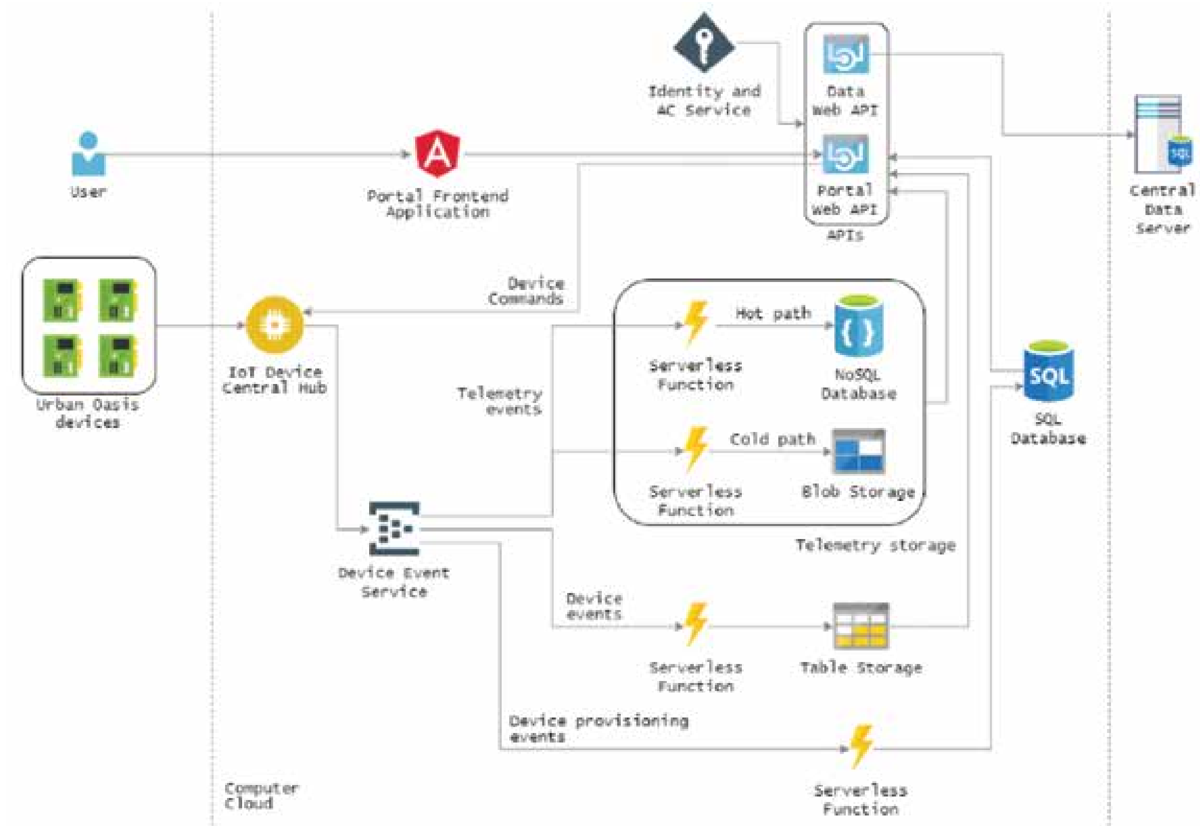



**Fig. 3.** Schematic of the IT system for collection and storage of the encapsulated design measured data.

Computer cloud layer: designed for three main functions: i) telemetry ingestion and analysis, ii) device maintenance and control and iii) presentation of aggregated data and analysis results. Individual devices are connected to the cloud services through a central node where the device telemetry and status messages are aggregated and routed to distinct endpoints.

Central data server: a local server that collects the telemetry data and status reports from multiple encapsulated design devices, archives the data and conducts the advanced data processing such as experiments scheduling or executing tailored AI algorithms. The server integrates the data from all the growing chambers and makes it available for advanced processing, i.e. modelling through the use of ML approaches. Along the data collected from the chambers via the cloud service, pictures obtained from the multi-spectral cameras are also stored on the central server computer, thus rounding up the available data from the plant development side.

## 5. Modeling of crop growth stages

With a significant amount of relevant data made available through the plant growth encapsulated design and the corresponding IT system, AI techniques, i.e. ML algorithms are employed to correlate the measured climate conditions with plant development indicators. In addition to the microclimate conditions and plant physiological identifiers data entries, short- and long-term weather forecasts are included in the dataset. The weather forecasts are provided by the Croatian Meteorological and Hydrological Service.

In accordance with the usual ML practice, the available dataset is divided into train, validation and test counterparts. Additionally, to significantly increase the reliability of prediction, models are classified and reduced to three parts, depending on the plant stage: i) germination, ii) plant formation and maturation, iii) grain maturation, and training is conducted on such divided data sets.

Several separate modules are developed based on the plant development indicators used as modelled outputs:

- yield prediction module,
- module for grain moisture prediction in current conditions and short-term prognosis,
- module for support in optimal pest treatment,
- module for long-term prediction of culture in climate change.

Once developed and tuned, the models will be publicly and interactively used through a web-based portal for predicting plant development under real and hypothetical climate conditions, with accumulated and archived feedback from farmers as additional data to tune the developed models.

Models of all three plant stage developments can be combined in order to offer insight into the overall plant development when new climate conditions are introduced. This option offers the possibility to simulate the wheat culture development in new environments that are likely to occur due to the climate changes already in effect. Such information can help in the determination of more fertile wheat cultivars and provide a general insight into crop development in the near future.

## 6. Conclusion

A system of encapsulated design devices for permutation of microclimate conditions and plant development monitoring is being elaborated. The system incorporates the concept of Internet of Things with real-time control and interfaces, and communication with a computer cloud that enable autonomous conduction of a large number of simultaneous experiments in microclimate zones of the device. It is used to rapidly gather a large amount of correlated data, thus enabling the artificial intelligence modelling of wheat development with respect to expected climate changes, i.e. predictive agriculture.

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