

Article

Autonomous Intelligent Irrigation Systems in Hop Plantations (Republic of Chuvashia, Russia)

Sergey A. Vasiliev ¹, Vladimir P. Filippov ¹ , Victor V. Alekseev ¹, Evgeny A. Maksimov ¹
and Evgeny V. Abakumov ^{2,3,*} 

¹ Faculty of Mechanical Engineering, I.N. Ulyanov Chuvash State University, Cheboksary 428000, Russia; vsa_21@mail.ru (S.A.V.); filippov_v_p@mail.ru (V.P.F.); av77@list.ru (V.V.A.); 89063830541@yandex.ru (E.A.M.)

² Department of Applied Ecology, St. Petersburg State University, St. Petersburg 199178, Russia

³ All-Russian Research Institute for Agricultural Microbiology, St. Petersburg 196608, Russia

* Correspondence: e_abakumov@mail.ru

Abstract

The possibility of implementing intelligent irrigation has a number of undeniable advantages, mainly including the fact that the time can be determined and the volume of irrigation water can be adapted to specific plant types on a specific soil. A neural network has been trained to describe the dynamics of soil moisture based on the basic soil water retention curve (SWRC). It is able to take into account a wide range of input data, such as the specific surface area of the solid phase of soils, porosity, humidity, etc., for a given initial soil moisture profile. Preference is given to a recurrent neural network, since this type works well with sequential data and is able to take into account time dependence and solve the problem of decaying gradients of soil hydrophysical properties. The neural network processes the vector of incoming signs—humidity, temperature, volume of incoming/outgoing water, etc.—and connects them with the dynamics of humidity from sensors located at different depths. When modeling mass–salt transfer with different boundary and initial conditions, the dependence of moisture retention on the moisture conductivity function is used, which allows us to calculate how moisture with dissolved nutrients moves through the soil under the influence of pressure and concentration gradients. Since the SWRC is constructed as a function of directly measured data, it is easy to set it for each point of interest in the field and at each depth. During modeling, the soil is divided into elementary volumes (from 2–3 mm to 1 cm), and an array with data sets is compiled at each point. The research was conducted in a real hop plantation (the village of Opytny, Tsivilsky district, Republic of Chuvashia). The values of the soil moisture sensors at different depths, together with the data from the portable weather station, are sent to the input of the neural network. According to the minimum allowable humidity for hops, the model predicts situations when humidity reaches critical values and initiates watering. Thus, the implemented approach makes it possible to automate irrigation management, increase water use efficiency and ensure optimal conditions for plants.

Keywords: solar panels; automation; intelligent irrigation and fertigation systems; water retention curve; Retisol



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1. Introduction

Agriculture consumes about 70% of the world's freshwater reserves, while irrigation efficiency remains low in many regions. Intelligent irrigation systems including modern

artificial intelligence have become the answer to this challenge. The evolution of irrigation methods [1] has gone from manual control to fully automated data-based systems. In their work, Gurmessa and Assefa [2], based on an analysis of publications found via Scopus, WoS, and Google Scholar, identified seven clusters dominated by IoT, machine learning (ML), and energy efficiency [3,4]. Naturally, irrigation systems, taking into account soil's hydrophysical foundations, evolve from calculations of moisture retention curves to intelligent controllers. The core of almost any "smart" irrigation system is a controller that, unlike a traditional timer, is able to learn and adapt [5]. A key review by Singh et al. (2025) [6] in *Discover Computing* compares classical proportional–integral–differential regulators with intelligent ones (neural network, fuzzy, evolutionary), demonstrating the superiority of the latter in the face of environmental uncertainty. A systematic review by Younes et al. (2024) [7] details the application of ML methods: from regression models for evapotranspiration estimation to ensemble methods and deep learning. At the same time, the work of Sharma et al. (2026) [8], devoted specifically to AI techniques for predicting evapotranspiration, a key parameter for calculating the water balance, deserves special attention.

The latest trends include the use of deep reinforcement learning (RL). Mukti et al. (2026) [9], in *Computers and Electronics in Agriculture*, show how Seq2Seq models in conjunction with RL can optimize irrigation regime in real time, adapting to short-term weather changes. Rahayu et al. (2026) [10] systematically analyze studies on weather-dependent deep learning and conclude that convolutional (CNN) and recurrent (LSTM) networks are often superior to classical ML, while RL is rarely used. Separately, it is worth noting hybrid systems based on fuzzy logic and cloud computing (see the article of the year for *Smart Agricultural Technology* (2025), i.e., [11]), which provide smooth irrigation control even with partial loss of sensor data. The architecture of most systems is based on a three-layer scheme: sensors → network → cloud (or Fuzzy layer). Recently published data [12–14] justified the need for further modernization of irrigation systems, including the use of local agroclimatic stations and solar panels. As was shown by Yu et al. (2025) [15], this architecture reduces delays and allows irrigation decisions to be made directly at the gateway, without constant communication with the center. A large-scale review by Mansoor et al. (2025) [16] in *Frontiers in Plant Science* summarizes the challenges: protocol standardization, data protection, and cost of deployment. An important addition to the data from stationary sensors is data from drones (UAVs), which provide operational monitoring of large areas. A review by Sharma et al. (2025) [17] in the journal *Drones* examines, in detail, the use of thermal, multispectral, and hyperspectral cameras to detect water stress in crops. The authors emphasize that the integration of data from UAVs, satellites (Sentinel, Landsat), and ground sensors into a single system allows for accurate humidity maps and differentiated water supply. The work of Al-Ani et al. (2025) [18], published in *IET Wireless Sensor Systems*, combines reviews on WSN and drones, highlighting scenarios of swarm interaction when the drone acts as a mobile repeater for disparate sensors.

The most promising direction, gaining momentum in 2025–2026, is the creation of digital counterparts of irrigated fields. The work of Bautista et al. (2025) [19] shows how ML models trained on historical data form a virtual copy of an agroecosystem, allowing various irrigation scenarios to be played out before they are actually applied. A systematic review (2025) in *Applied Sciences* [20] summarizes many studies on digital twins in water resource management, noting that, at the moment, most implementations are at the prototype stage, and full-scale implementations are rare. Additionally, ref. [21], published in *Procedia Computer Science* (2025), demonstrates a specific case of a digital twin based on LSTM and humidity sensors, which reduced water consumption by 27% compared to a fixed water supply. Sarayani et al. (2025) [22] described a drip irrigation system in a soilless

crop (hydroponics), where the irrigation decision is made based on the percentage of drainage—a non-trivial task requiring a quick response. It has been emphasized that merging heterogeneous data for modeling and optimization of energy supply for irrigation is necessary nowadays [23–25].

This analysis allows us to draw the following conclusions: (1) intelligent irrigation systems are confidently moving from the stage of scientific prototypes to pilot implementations; (2) the dominant technological blocks are IoT data collection and ML decision-making; and (3) there are problems related to the lack of long-term field trials (more than 2–3 seasons), and the use of reinforcement learning methods in real controllers is rare (see Abdollahi et al. (2021) [26]).

2. Materials and Methods

An autonomous intelligent irrigation system is implemented according to the flowchart below (Figure 1). Solar panels installed on the hop plantation, if necessary, provide energy to humidity and lighting sensors, power a portable weather station, and pump water into a water tower, while also turning the water supply to the irrigation network on and off. An energy-efficient minicomputer is powered through a stabilizing unit. The basic hydrophysical characteristic constructed for hopberry soils serves as the core for modeling moisture dynamics during soil drying and irrigation. A neural network is trained on its data, which, according to the vector of incoming data, initiates watering. In this paper, attention is mainly paid to the implementation of the intelligent part of the flowchart, which is responsible for processing sensor data and turning the water supply on/off.

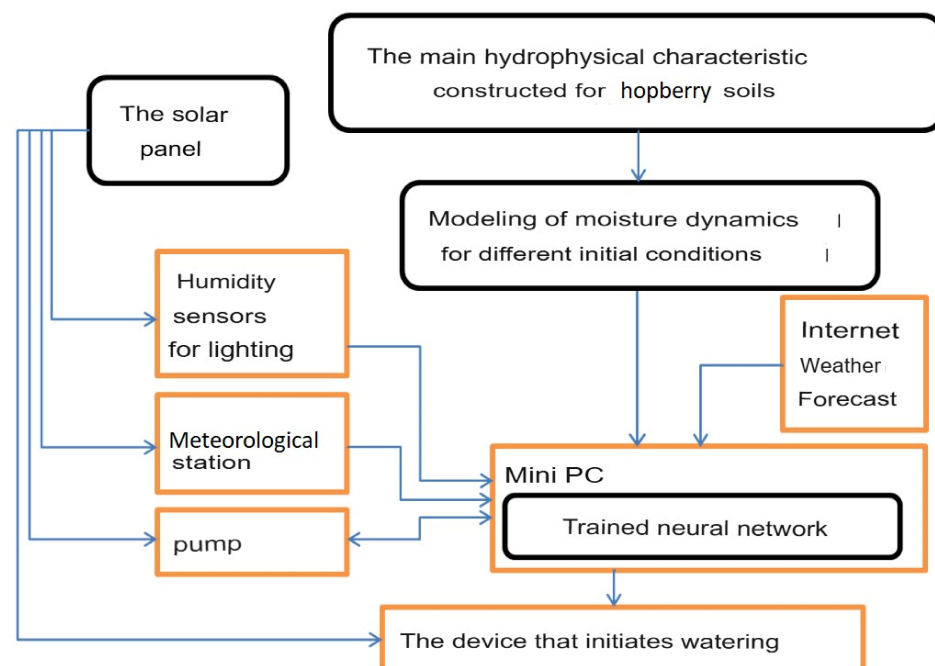


Figure 1. Block diagram of the intelligent irrigation system.

Modern technologies make it possible to use artificial intelligence (AI) to predict crop watering by analyzing large amounts of data. To identify optimal moisture management scenarios and improve the accuracy and efficiency of water management, AI systems need the following: (1) analysis of soil moisture data at different points of the field, including weather data such as temperature, humidity, precipitation, solar radiation, wind speed and terrain features, as well as soil type and soil profile structure details; (2) information about the current state of the field and the water needs of the plant species of interest; (3) training

(to show how much water is required for specific areas during different plant growing seasons); (4) correct identification of areas with excessive or insufficient water consumption; and (5) drought prediction and adaptation to weather changes, allowing you to change the irrigation schedule in advance.

There are a number of examples of AI use in predicting irrigation of agricultural plants. The LSTM-based model has a higher accuracy in predicting humidity forecasts compared to classical methods (ARIMA).

Intelligent irrigation, as a tool that determines plants' need for water and the appropriate volume, basically has dependencies that determine the dynamics of soil moisture. Therefore, for the task of describing the dynamics of soil moisture and predicting irrigation, a neural network that can model time dependencies and take into account multifactorial input data (weather conditions, soil type and condition, current moisture distribution, etc.) is needed. Intelligent irrigation, as a tool that determines the need for water for plants and its volume, basically has dependencies that determine the dynamics of soil moisture.

Of the known neural network architectures, recurrent neural networks (RNNs) with LSTM or GRU are preferred. This is due to the fact that RNNs work well with sequential data and are able to take into account time dependence. LSTM (Long Short-Term Memory)—which stores the previous state in memory at each step and uses it to process the current input value—and GRU (Gated Recurrent Unit), which determines which part of the past state to forget, while the update gate controls how much new information affects the cell state—are special types of recurrent networks. They can also remember long-term dependencies, which is important for soil moisture dynamics (for example, accounting for irrigation or precipitation effects). Thus, to train a neural network, we need to have a sequence of time steps (these can be simulation results corresponding to certain time intervals). At each step, vectors of features such as humidity, temperature, volume of incoming/outgoing water, etc., are received (spatial distribution). So, the input layer of the neural network accepts a sequence of feature vectors. Next, the normalization layer (LayerNorm) is used to stabilize learning. Then, depending on the amount of data, there should be LSTM/GRU layers. The number of neurons is adjusted experimentally depending on the completeness of the description. Another Dropout layer is needed to prevent overfitting. After the fully connected dense layer, which converts the LSTM output into a forecast, comes the output layer. Such an architecture is able to take into account complex time dependencies and combinations of influencing factors.

For the optimal growth and development of hops (*Humulus lupulus* L.), regular yet moderate irrigation is of decisive importance, serving to maintain the soil in a moist but not waterlogged state. This crop is hygrophilous and exhibits poor tolerance to both drought and root-zone water stagnation. Approximately 60% of the plant's water uptake occurs in the 0–60 cm soil horizon, while an additional 40% is extracted in the 60–130 cm layer. While the overall favorable annual precipitation and/or irrigation rate for hops ranges from 450 to 650 mm, the critical period from mid-July to mid-August requires approximately 90–100 mm of precipitation or irrigation water to achieve high field yields.

The lower limit of plant-available moisture, defined as the permanent wilting point (PWP), has not been specifically documented in the open literature for hops. In international agronomic standards, the PWP is conventionally associated with a soil water (matric) potential of approximately -1500 kPa (or -15 bar). However, this value is not an intrinsic constant and varies for a given crop depending on soil type and textural composition. The specific hydrophysical properties of a given soil are characterized by its soil water retention curve (SWRC); consequently, the PWP can be determined by identifying the moisture content corresponding to the -1500 kPa potential on the SWRC. Depending on soil depth—which influences porosity and the specific surface area of soil particles—the critical

moisture threshold for hops fluctuates between 0.24 and 0.28 (expressed as volumetric water content, $\text{m}^3 \cdot \text{m}^{-3}$). The approach of soil moisture toward this threshold serves as a reliable indicator for the initiation of irrigation.

Knowledge of the basic hydrophysical characteristics for a particular soil makes it possible to simulate both the movement of moisture in the soil and the transfer of nutrients. The moisture retention curve is a fundamental hydrophysical characteristic that relates the volume moisture content of the soil to the matrix potential (pressure). For intelligent irrigation systems, knowledge of soil and hydrological characteristics makes it possible to calibrate inexpensive capacitive humidity sensors, calculate irrigation response thresholds (for example, watering when the potential is reduced to -30 kPa), and simulate vertical and horizontal moisture transfers. Since, depending on the moisture content, water in the soil passes through various energy states, which are described by various rheological models, there is scope for a differentiated approach for modeling mass–salt transfer. Sysuev et al. (2013) [27] proposed an aerodynamic method for obtaining a soil moisture retention curve (SWRC), which differs from traditional methods in that it has a shorter measurement time and the ability to work in the field. Such models require a minimum set of input parameters (addition density, granulometric composition) and can be integrated into on-board microcontrollers of drip irrigation systems for rapid recalculation of sensor readings. Modeling of various boundary and initial conditions, in some cases, allows us to obtain results corresponding to non-trivial cases that are not usually described in the scientific literature. One such example is the modeling of salt rim formation during fertigation by Dubenok et al. (2023) [28] or features of the occurrence of runoff during irrigation of sloping lands (Alekseev et al. (2020) [29]), as well as the formation of a soil crust. Irrigation water, and therefore, if present, the minerals dissolved in it, move in the soil according to the laws of hydrophysics. In this regard, the modeling is based on the basic hydrophysical characteristics of soils, which allows us to calculate how moisture with dissolved nutrients moves through the soil under the influence of pressure gradients. The pressure of soil moisture through the amount of liquid density is related to the moisture potential. In this paper, we consider the potential as the sum of the components $\psi' + \psi'' + \psi'''$, where ψ' is the potential caused by the interaction of moisture with the solid phase of the soil, ψ'' is the potential caused by the interaction of moisture from the soil air, and ψ''' is the potential associated with the presence of dissolved mineral elements that lead to osmotic pressure. Therefore, the dependence of the basic hydrophysical characteristic can be described by the following formula [30,31]:

$$\psi = \psi' + \psi'' + \psi''' = \frac{A\Omega_0^3}{\rho w^3} + \frac{\Omega_0 \sigma_{lg}}{\rho} D(w, \Pi_0) + \frac{RT}{\rho} \left(\frac{C}{M^*} + \frac{C^2 \rho}{M(\rho^*)^2} \left(\frac{1}{2} - \mu \right) \right)$$

where ρ —water density; σ_{lg} —coefficient of surface tension (water–air); Ω_0 —volumetric specific surface area; w —volumetric humidity; A —Hammaker’s constant; μ —constant; Π_0 —porosity of a dry sample; $D(w, \Pi_0)$ —a function that takes into account the granulometric composition of the soil; M —molar mass of water; M^* —molar mass of dissolved substance; C —concentration of dissolved substances; kg/m^3 ; and R —universal gas constant; T —temperature, K.

It is noteworthy that all the parameters in Formula (1) are directly (and easily) measurable for each point of the field of interest and at each depth. During the simulation, the gravitational potential was represented by $g\Delta h$. When calculating the potential difference, soil moisture was added when calculating the transfer from layer to layer and was not added when calculating the transfer inside the layer Δh . Figure 2 shows the moisture conductivity function for light gray forest soil (Retisol).

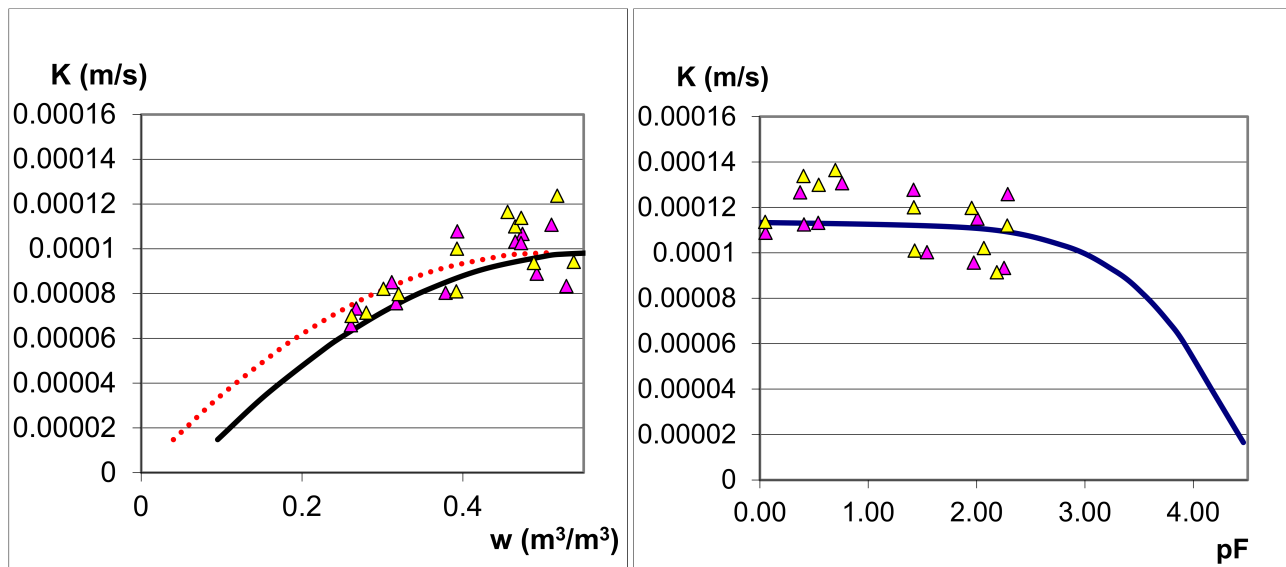


Figure 2. Relation of $K(w)$ and $K(pF)$ for Retisol. Δ —experimental values; the dotted line shows the dependence without taking into account the volume of strongly bound water (w^*). Different colors of triangles correspond to different groups of experiments conducted on the same soil sample, under the same conditions.

It is important to emphasize that the above models of moisture retention, which make it possible to calculate the contours of humidification and the distribution of salts supplied with irrigation water, can serve as physical a priori knowledge for hybrid neural networks (physics-informed neural networks, PINNs), which increases the generalizing ability of AI beyond the training sample.

The speed of modern calculations makes it possible, using a small time step, to apply the finite difference method and abandon the differential equations of mass transfer. The essence of the modeling lies in the fact that the studied volume of soil is divided into elementary volumes (depending on the required detail and each specific case from 2–3 mm to 1 cm). A uniform grid function is created—an array with certain data sets at each point. Such data include the volume-specific surface area of soil particles, soil porosity, current humidity, the concentration of dissolved minerals, the values of soil moisture potential and coefficient of moisture conductivity, temperature, etc. At each iteration, all the changing values are recalculated. After calculating the volume of moisture flowing between neighboring nodes, the concentration of dissolved substances is recalculated. In addition, according to the thermal balance, the temperature values in each node are recalculated. All this makes it possible to recalculate the osmotic pressure, the coefficient of surface tension and the viscosity of soil moisture, since their dependences on temperature and concentration are known.

In conditions of low soil moisture content (i.e., at humidity values close to hygroscopic), the bulk of the water is in an adsorbed state, forming thin films on the surface of solid mineral particles. The thickness of such films is, as a rule, 4–5 monomolecular layers, which corresponds to a value of the order of 10^{-7} m. In this state, water molecules are characterized by a high degree of structural order and dense packing due to the action of surface forces (van der Waals interactions and electrostatic potentials). Due to the rigid spatial orientation of the molecules, such film moisture is unable to perform the function of a solvent for ionic compounds: the lack of free volume and increased viscosity prevent the hydration and dissociation of salts.

With an increase in soil moisture, accompanied by an increase in the thickness of the water film to values of the order of $h + \Delta h \approx 10^{-8}$ m, the transitional layer Δh begins

to form, in which the molecular structure gradually loses its strict order. In this layer, the solubility of salts increases and reaches values characteristic of ordinary (bulk) water. Humidity W_0 , corresponding to the thickness of layer h , can be determined in several independent ways. The first method is based on passing an electric current through a soil sample. The second approach is to solve a system of equations that includes the soil water retention curve $pF(w)$ and the empirical ratio $pF = 5.2 + 3w$, which describes the maximum adsorption capacity of soil material.

3. Results and Discussion

Automation of plant watering is performed using neural network training. The training is based on the dynamics of soil moisture values at different depths and for different initial moisture profiles. The data is preprocessed first (cleaning and normalization), and then the training set and test data are selected. The process of learning a model with a certain loss function involves selecting the number of layers and the number of neurons in a layer. The quality of the predictions is evaluated. To maintain optimal humidity, we use the humidity value of a stable wilt of plants. For hops, this is usually about 60–70%, allowing for variation, depending on the specific growing conditions (soil type and porosity). Thus, conditions for stress-free plants, ensuring their growth, are achieved.

A hop plantation has a network of points where soil moisture sensors are installed at depths of 0.1, 0.33, 0.66, and 1 m. Soil moisture is measured in real time with an interval of 1 h. The weather station provides data on temperature, humidity, precipitation, solar radiation, and wind speed. Drip irrigation is considered to be the most effective in terms of water conservation; however, its dynamics (the formation of a moisture contour, the movement of the moisture front) strongly depend on the properties of the soil and the supply mode. Examples of simulation results are shown in the figure below. The initial conditions are as follows: soil porosity decreased almost uniformly from 0.62 on the surface to 0.48 at a depth of 0.5 m, while the specific surface area also increased uniformly with a depth of $44 \text{ m}^2/\text{g}$ on the surface to $49 \text{ m}^2/\text{g}$ at a depth of 0.50 m. The dynamics of volume humidity during drip irrigation for various initial moisture profiles and distances presented on the Figure 3.

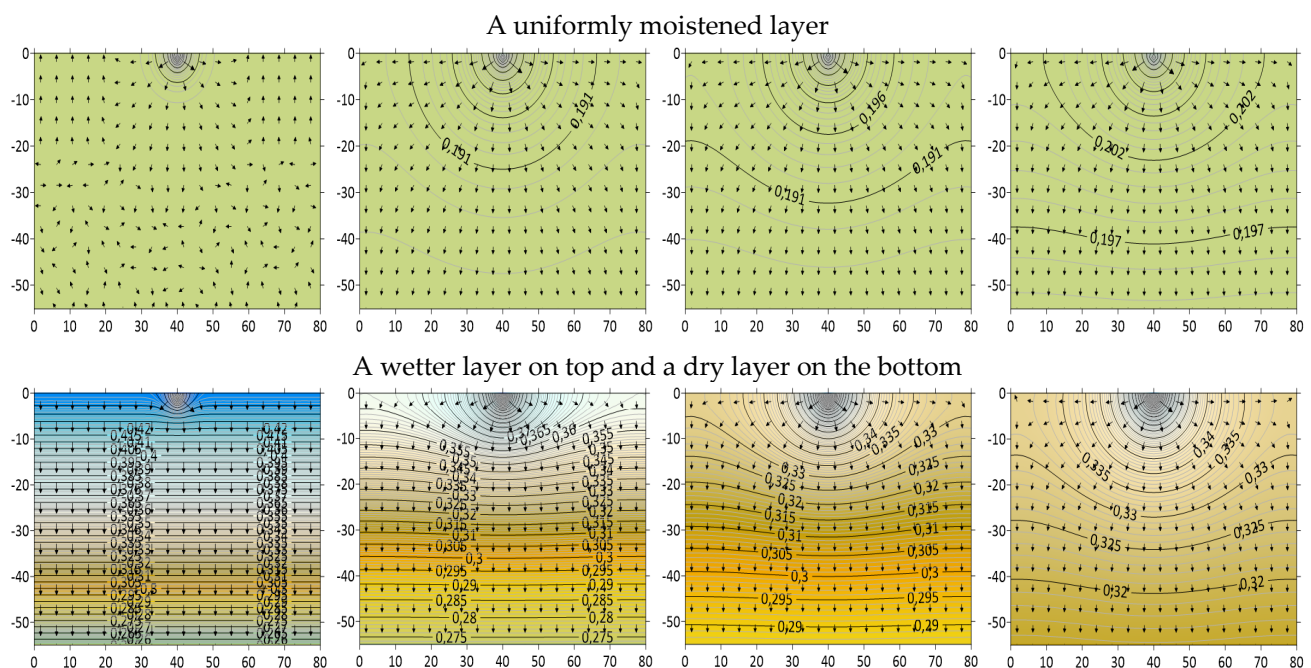


Figure 3. Cont.

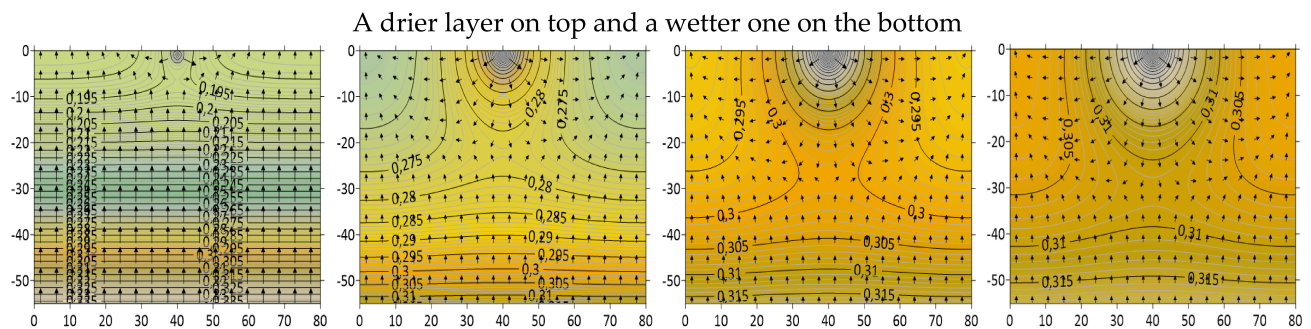


Figure 3. Dynamics of volume humidity (cm^3 of water/ cm^3 of soil) during drip irrigation for various initial moisture profiles; distances (cm) are plotted horizontally and vertically. The intensity of the pattern color changes in proportion to the change in the value of the described parameter.

Figure 4 shows the results of modeling drip moisture in the soil, as well as drying for the three most markedly different cases of initial moisture distribution in the soil: (1) humidity is evenly distributed, (2) humidity decreases with depth, and (3) humidity increases with depth.

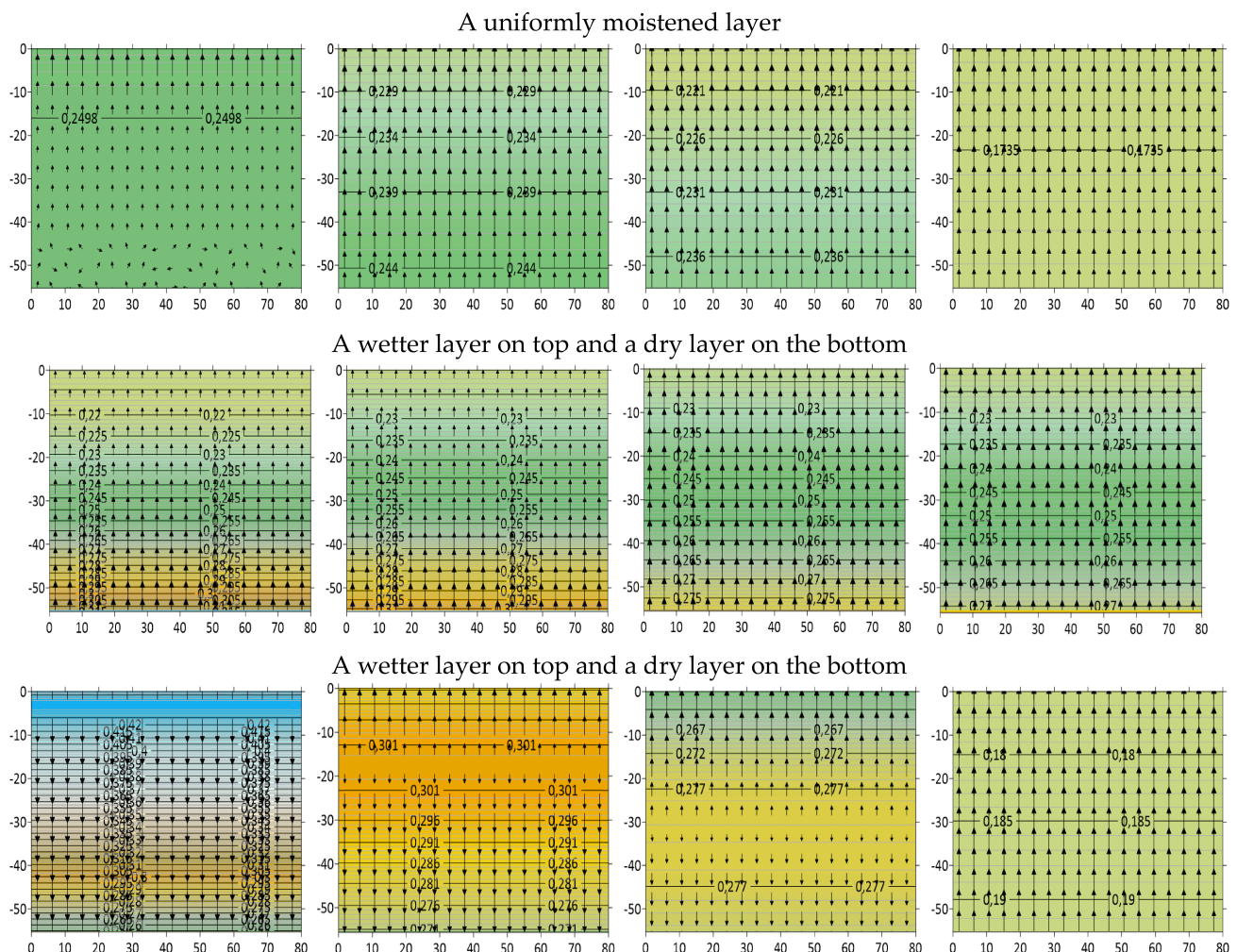


Figure 4. Dynamics of volume humidity (cm^3 of water/ cm^3 of soil) during soil drying; distances (cm) are plotted horizontally and vertically for different initial moisture profiles. The intensity of the pattern color changes in proportion to the change in the value of the described parameter.

To offer a statistical description of the validation set, it encompasses a continuous test period of 78 days (from 1 June to 17 August, covering the critical growth stages of flowering

and cone development). It comprises 12,480 individual data points (one reading per 10 min from eight soil moisture sensors distributed across four field plots).

Seasonal coverage includes a wide range of meteorological conditions: three dry spells (each lasting 5–7 days with no precipitation), two heavy rainfall events (>25 mm/day), and daily temperatures ranging from 14 °C to 34 °C. This ensures that the validation set captures both typical and extreme scenarios relevant to irrigation scheduling.

Model performance under unseen conditions was evaluated against independent field measurements not used during training. The model achieved an RMSE of $0.032\text{ m}^3\cdot\text{m}^{-3}$ and an R^2 of 0.89 for predicting volumetric soil water content. For the binary irrigation decision (irrigate/not irrigate), the F1-score was 0.93. Performance degraded only slightly (RMSE + 0.005) during the hottest week, indicating robust generalization. Time-based cross-validation (forward-chaining) further confirmed that the model maintains its accuracy when tested on data from weeks not seen in training, with a mean absolute error below $0.04\text{ m}^3\cdot\text{m}^{-3}$ across all held-out temporal folds.

When justifying irrigation standards and calculating the concentrations of mineral fertilizers applied with irrigation water, it is necessary to take into account the spatial and temporal distribution of moisture in the soil profile at the initial time (i.e., before the start of irrigation). This initial distribution is determined by the previous moisture regime, granulometric composition, soil structure, and hydrological conditions. In case of unsatisfactory uniformity of moisture or the presence of areas with critically low humidity, it is recommended to carry out preliminary agromelioration soil preparation (for example, deep loosening or crevicing) aimed at leveling the water–physical properties.

An important feature of soil drying after watering with water containing dissolved minerals (including macro- and microelements of nutrition) is the phenomenon of local accumulation of salts. It has been experimentally established that the bulk of salts is concentrated at the narrow interface between the dry and wet zones of the soil—in the area characterized by the maximum moisture gradient ($\partial w/\partial z \rightarrow \max$). It is here that the so-called “salt rim” (or “salt front”) is formed, which is clearly visible during visual inspection of the soil section in the form of a light band of crystalline deposits. The physical essence of the process is as follows: If there is a significant drop in capillary sorption pressure (matrix potential) between the wet and dry zones, an intense flow of moisture towards the evaporating surface occurs. If a salt solution is present in the wet zone at the initial moment, then as the moisture moves towards the evaporation front, the solvent (water) is removed, and the dissolved substances remain.

As a result, an area with a sharply increased concentration of salts is created directly at the interface of the phases. The osmotic gradient that occurs in this case causes an additional influx of moisture from neighboring layers—soil moisture, figuratively speaking, is “pumped” into the zone of high ionic strength. The concentration of salts in this zone reaches values that make sure almost the entire volume of the pore space is filled with crystalline salts (usually easily soluble ones—chlorides, sulfates, carbonates). This salt horizon is often clearly visible to the naked eye due to the high reflectivity of crystals and the change in soil color.

Due to the practical significance of this phenomenon (the risk of soil salinization, reduced yields, and degradation of reclamation systems), special field and laboratory experiments were conducted, and a computational program was developed that simulates the redistribution of salts during soil drying. The program is based on the numerical solution of moisture transfer equations (Richards equation) and salt transfer (convection–diffusion equation), taking into account the nonlinear dependence of moisture and diffusion coefficients on humidity.

The developed software allows you to set a wide range of initial and boundary conditions, including (1) moisture distribution profiles over soil depth (from the surface to the lower boundary of the active layer); (2) initial concentrations of nutrients (nitrogen, phosphorus, potassium, trace elements) in the soil solution; (3) irrigation parameters, such as irrigation intensity (mm/hour), duration of water supply, and frequency; and (4) the hydrophysical characteristics of the soil (water retention curve, filtration coefficient, porosity, specific surface area).

With the help of this program, by purposefully selecting the initial conditions (pre-irrigation humidity, depth of groundwater) and rational irrigation regimes (frequency, norms, irrigation methods), it is possible to significantly reduce the intensity of the formation of salt ridges and compacted salt horizons or completely prevent their formation. The practical implementation of such calculations makes it possible to optimize land reclamation measures (flushing, drainage) and increase the efficiency of fertilizer use, minimizing environmental risks.

After comparing the simulation results with experimental data, the numerical coefficients were adjusted to reduce discrepancies. Of course, to train the neural network, a fairly wide range of initial conditions was used, both for irrigation intensity and initial moisture distributions over depth, which were set by various nonlinear dependencies.

In a similar way (for different initial profiles of moisture, temperature, and humidity above the soil), a neural network was trained for cases of soil drying and crust formation. For hops growing on this particular soil, the minimum allowable and optimal moisture levels are determined. The model learns to recognize situations when humidity reaches critical values and initiate watering. Thus, the implemented approach makes it possible, through intelligent forecasting, to automate irrigation management, increase water use efficiency and ensure optimal conditions for plants.

4. Conclusions

An intelligent irrigation system for hop orchards (*Humulus lupulus* L. from a hop plantation) that automatically determines the start time, intensity, and total volume of water supply has been developed. These parameters are dynamically adapted to the current physiological needs of hop plants, which depend on growth stage, weather conditions, and soil hydrophysical properties. The system analyses real-time data from sensors measuring soil moisture at multiple depths, surface air and soil temperatures, and the water balance (incoming precipitation/irrigation vs. evapotranspiration and drainage). Using physiological thresholds for minimum allowable moisture, the system predicts when root-zone moisture drops below critical levels and initiates irrigation proactively to prevent plant stress. A key advantage is its minimal input requirements: only soil bulk density, soil texture (sand/silt/clay fractions), and initial moisture profile are needed. The computational approach avoids iterative solutions of complex differential equations, enabling deployment on low-power microcontrollers (Arduino, ESP32, STM32) without cloud dependence, thus ensuring autonomy and reliability in the field. The algorithms are also compatible with broader digital agriculture applications, including yield prediction and digital soil twins.

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