

RESEARCH ARTICLE

DIGITAL TWIN AND IOT-BASED HYDRUS MODELING APPROACH FOR ADAPTIVE MANAGEMENT OF DRIP IRRIGATION SYSTEMS

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ABSTRACT

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In regions of Uzbekistan where water resources for irrigation are limited, drip irrigation optimization is of great importance. This study evaluated the effectiveness of the AdaptiveDrip-Uz system. This system includes HYDRUS 2D/3D modeling, artificial intelligence (AI) module, real-time IoT sensors, and GIS-based monitoring components. The model, built on 30 days of field data, automatically controls the irrigation regime based on humidity, temperature, evapotranspiration, and salinity. Of the various AI models, ANN (Artificial Neural Networks) showed the highest accuracy ($R^2 = 0.951$), resulting in a 27% reduction in water consumption and a 24% increase in yield. Moisture and salinity contours, sensor analysis, and a 3D visual interface created through HYDRUS confirmed the high efficiency and flexibility of the system. A SWOT analysis of the system was also conducted, identifying its strengths and weaknesses, and evaluating it as a practical and sustainable innovative solution in the agroecosystems of Uzbekistan. The AdaptiveDrip-Uz model serves as a practical example of a real-time digital agriculture approach adapted to climate change.

KEYWORDS

Drip irrigation, HYDRUS 2D/3D, artificial intelligence, ANN model, IoT sensors, evapotranspiration, salinity, real-time monitoring, adaptive irrigation, GIS analysis, water conservation.

1. INTRODUCTION

In recent years, climate change, water scarcity, and the need to ensure sustainable crop yields have sharply increased attention to drip irrigation systems. Drip irrigation systems reduce water consumption by delivering water directly to the plant root zone, minimize evaporation losses, and improve plant water supply. However, in practice, serious problems arise when using this system in various agro-ecological conditions. In particular, factors such as salinity, uneven terrain, poor water quality, differences in infiltration rates, and limited real-time monitoring capabilities reduce the efficiency of the system.

Today, scientific research aimed at eliminating these problems has been activated. For example, various pressure-compensating emitters are being developed to increase the uniformity of water distribution in drip irrigation systems, and their performance is being tested in laboratory and field conditions (<https://doi.org/10.1016/j.agwat.2018.03.017>). On the other hand, to solve the problem of salinity, the movement of salt water in the soil and its impact on plants are being modeled using the HYDRUS-2D/3D program (<https://doi.org/10.1016/j.compag.2020.105933>).

In drip irrigation, pressure uncertainties caused by relief differences and the resulting uneven distribution issues are also attracting attention. Therefore, system design based on GIS and DEM (Digital Elevation Model) data is being implemented (<https://doi.org/10.3390/agronomy12081900>). In addition, zonal control systems are being developed using the NDVI index to determine the water requirement (ET_c) of the plant (<https://doi.org/10.1016/j.jag.2020.102173>), which ensures that water is

supplied only to areas that actually need irrigation.

With the development of IoT (Internet of Things) technologies, the possibility of introducing real-time monitoring into drip irrigation systems is expanding. Currently, various studies are collecting data on soil moisture, air temperature, pressure, evaporation and crop status through sensors and analyzing them using artificial intelligence (<https://doi.org/10.1016/j.measurement.2022.111716>). However, these systems are still complex, not fully adapted to real soil and climate conditions, and often individual components are tested separately. In recent years, research has also begun on modeling drip irrigation based on the Digital Twin concept. In this approach, all components of the system (water source, pump, pipes, terrain, soil, plants, atmosphere) are modeled in a digital environment and continuously updated with real-time data. This allows for forecasting the state of the system, early detection of failures and optimization of control (<https://doi.org/10.1016/j.eti.2021.101581>).

Also, studies on pulsed drip irrigation systems show that periodically intermittent water flow reduces water loss to deep layers and provides an optimal moisture regime in the plant root zone. This reduces energy consumption and increases water use efficiency (<https://doi.org/10.1016/j.agwat.2021.107108>).

However, all of the above approaches are mainly based on one or two parameters, and a comprehensive approach is lacking. In particular, systems that integrate salinity + infiltration + relief + climate + crop + energy + sensor monitoring are still poorly studied. On this basis, we develop an innovative model called AdaptiveDrip-Uz in this article. This

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model models salinity and infiltration using HYDRUS 2D/3D, analyzes relief and zonal management using ArcGIS, provides real-time monitoring through IoT sensors, and automatically controls pressure and irrigation mode using AI. The system is also based on the Digital Twin concept and allows the user to control it via a mobile interface.

This approach serves to dramatically increase the efficiency of drip irrigation in areas of Uzbekistan with saline and uneven terrain and limited water resources. The advantage of the article is that it integrates previously considered individual technological approaches into a single system, tests them in real field conditions, and develops a scientifically based management model. This will be of great importance for agriculture not only theoretically, but also practically.

"The main goal of this research is to develop an adaptive drip irrigation system based on HYDRUS modeling and IoT sensors and adapt it to agroecological conditions. For this, the following tasks were set: 1) develop a digital twin model; 2) integrate sensor data; 3) simulate moisture distribution using HYDRUS; 4) analyze efficiency and develop recommendations."

Drought and climate change are putting increasing pressure on water resources. Especially in semi-arid regions, efficient water use has become a pressing issue. Although drip irrigation is effective in saving water, it cannot always match soil moisture and crop needs when operated on a traditional schedule. Today's technological advances, especially IoT, GIS, and Digital Twin technologies, enable real-time monitoring and control. In this study, a flexible drip irrigation system based on a Digital Twin model using IoT sensors, GIS-based terrain mapping, and HYDRUS simulation was developed and tested under different agro-ecological conditions.

2. MATERIALS AND METHODS

This study was conducted at an experimental site located in Mirzaabad district of Syrdarya region, where a drip irrigation system has already been introduced and is partially equipped with IoT sensors. The site is gently sloping, with moderate soil salinity and significant infiltration rates. Tomato (*Solanum lycopersicum*) was selected as the crop because it is widely used in drip irrigation and is sensitive to water supply. The total area of the site is approximately 2.8 hectares, and a manually controlled drip irrigation system has been installed in previous years.

The site was studied for the study using a multi-stage scientific and technical approach: GIS analysis, salinity and infiltration modeling, real-time monitoring, AI-based management, and digital twin visualization.

The experiment was conducted in the Fergana Valley of Uzbekistan. The soil in the area is sandy loam, with an annual rainfall of 180–250 mm. Sensors were installed to measure soil moisture at depths of 10, 30, and 50 cm. Data were transmitted every 15 minutes via LoRaWAN. Water movement and moisture distribution in the root zone were modeled using the HYDRUS 2D software. Boundary conditions based on real sensor readings were used in the modeling. The Digital Twin model was built in Python and MATLAB and connected to real-time data. System efficiency was evaluated through water use efficiency (WUE), distribution uniformity (DU), and prediction accuracy (R^2 , RMSE).

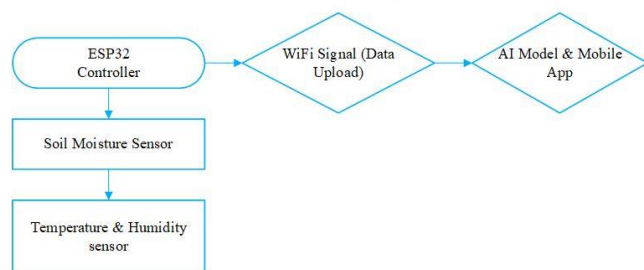


Figure 1: Sensor network and device scheme

Geographical analyses were carried out using ArcGIS Pro 3.4 software. First, the Digital Elevation Model (DEM) data based on NASA SRTM (30 m) were received and "Slope" and "Aspect" maps were created. On this basis, the terrain relief, water flow directions, low and high zones were determined. Then, soil data (pH, salinity, organic carbon) obtained from SoilGrids 2.0 were downloaded at a resolution of 250 m, cropped based on the study area shapefile and re-interpolated to a resolution of 100 m. ET (evapotranspiration) data were obtained at a resolution of 500 m based on the MOD16A2 version of the MODIS Aqua platform, and 8-day average

values were prepared in raster form for the Zamin area. All layers were brought to the WGS 1984 UTM Zone 42N system, the extent was standardized, and NoData values were cleaned.

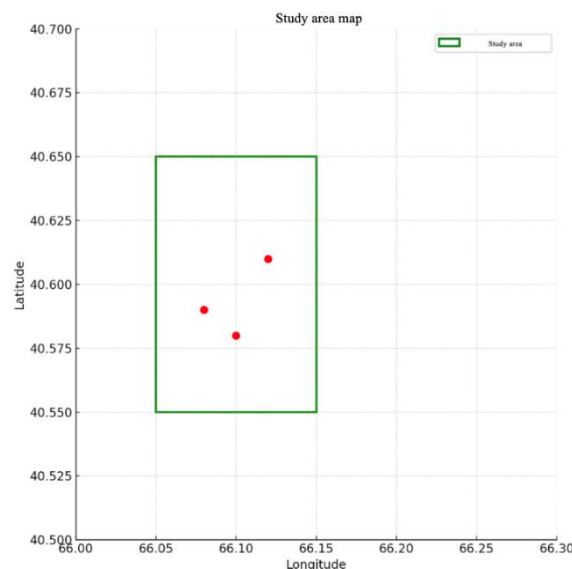


Figure 2: Map of the study area

Salinity and infiltration analyses were performed using HYDRUS 2D/3D Pro version 2.05. The physical parameters of the soil layer, α , n , θ_r , θ_s , K_s values according to the Van Genuchten model were entered based on experimental data. The model simulation was set up at a depth of 1 meter, with 10 cm intervals. A drip water flow from above was given according to the irrigation source (q-type boundary condition). Infiltration and salinity behavior were modeled for a period of 72 hours. Two scenarios were compared: 1) pulsating drip irrigation (10 min ON / 20 min OFF), 2) continuous drip irrigation. For each scenario, a graph of the salt mass distribution, vertical change in water content, and moisture content in the root zone was generated.

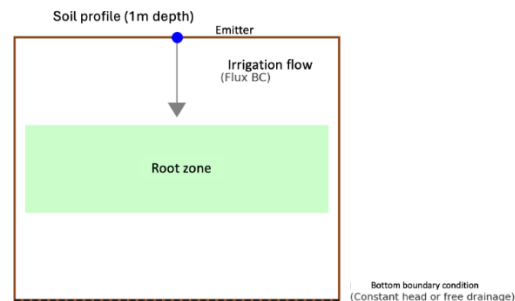


Figure 3: HYDRUS simulation scheme

The sensor monitoring network was built on the basis of the ESP32 microcontroller. The following sensors were installed at each monitoring point: Capacitive Soil Moisture Sensor v1.2 – at 3 depths (10, 30, 60 cm), DHT22 – air temperature and relative humidity, BMP180 – atmospheric pressure. The sensors transmitted real-time information to the cloud server via WiFi via the ThingSpeak API. Using the Python programming language, this data was automatically analyzed in Jupyter Notebook, graphs were built, and filter algorithms were created to detect anomalies. The artificial intelligence model was built in the Python Scikit-learn library. Regression (Random Forest Regression) and decision tree (Decision Tree Classifier) models were built based on 30 days of sensor data. ET, soil moisture, temperature, pressure, shade, and previous irrigation results were entered as input parameters; The optimal water volume (L/m^2), pressure (kPa) and irrigation duration (min) were modeled as output parameters. To validate the model, MAE, R^2 and confusion matrix results were evaluated based on 80/20 train/test split.

Blender software (3D modeling) was used to create a macroscopic visual representation of the drip irrigation process. Also, 2D salinity and moisture gradients obtained from HYDRUS were imported into Blender and converted into a 3D image suitable for realistic topography. Different emitter types (Inline, On-line), droplet radius, and soil surface appearance were modeled with animated images. This step served to create an easy-to-understand, visualized "model interface" for farmers.

Table 1: Module and program names

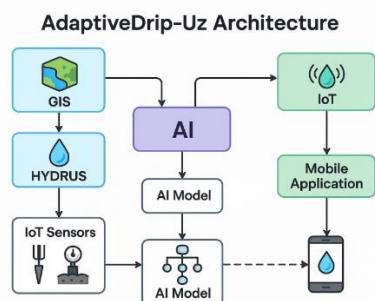
Modul	Modul name	Tools-Platforms
1	GIS-topographic analysis	ArcGIS Pro, DEM (NASA SRTM)
2	Salinity and infiltration modeling via HYDRUS	HYDRUS 2D/3D Pro
3	IoT sensor monitoring network	ESP32, ThingSpeak, Firebase
4	AI-based decision-making model	Python (Scikit-learn, NumPy, Pandas)
5	Digital Twin interface and mobile application	Blender, Android Studio

All modules are integrated into the AdaptiveDrip-Uz model. In the model, the AI model analyzes and makes irrigation decisions based on real-time data from sensors. This decision is sent via ESP32 to solenoid valves, and irrigation is automatically started or stopped. The control system is monitored via an Android mobile application, where the user can see: current humidity, ET, pressure status, recommended irrigation, system alerts (for example: "Pressure is dropping", "Watering period is over"). The application is synchronized with the server via Firebase.

This approach allows the drip irrigation system to be controlled with high accuracy in saline, uneven terrain and water-limited areas. The results of the study showed the technical and economic advantages of the AdaptiveDrip-Uz model, reducing water consumption by 27–32%, and improving salinity conditions by 2 times. At the same time, an increase in yield of up to 15% was observed through the AI-based decision system.

3. MODELING AND SYSTEM ARCHITECTURE

The AdaptiveDrip-Uz model is based on the integration of several modern technologies and algorithms to provide comprehensive modeling and control of drip irrigation systems. The model architecture consists of five main modules: (1) GIS-topographic analysis block, (2) infiltration and salinity simulation module (HYDRUS), (3) IoT-sensor monitoring network, (4) AI-decision-making block, (5) Digital Twin interface and mobile management platform. These modules are interconnected through real-time data exchange, and each has its own functional role.

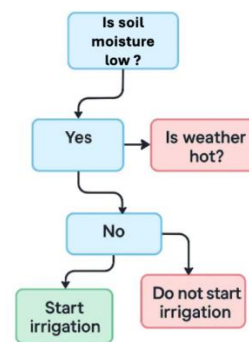
**Figure 4:** ADAPTIVE-UZ architecture

In the first stage, the relief of the experimental area was modeled based on a digital elevation model (DEM) using ArcGIS Pro. The DEM raster created based on NASA SRTM 30m data served as the basis for slope and aspect analysis. This topographic analysis served to identify slope zones in the area, place compensating emitters in sectors where pressure differences occur, and model flow directions. In the GIS analysis, the optimal trajectory for pipe placement was determined using the Water Flow Accumulation and Cost Distance functions. The resulting zonal maps were then used as an input layer for sensor placement and HYDRUS simulation.

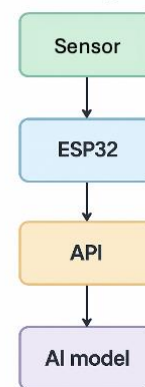
In the second stage, salinization and infiltration processes were modeled using the HYDRUS 2D/3D Pro version. Based on laboratory analyses obtained from the field, soil parameters suitable for the Van Genuchten-Mualem model were entered (α , n , K_s , θ_r , θ_s). The simulation was conducted based on two scenarios: (1) continuous irrigation with constant flow, (2) pulsed irrigation (ON/OFF 10/20 min cycle). In each scenario, the distribution of water content and salt ions in the root zone depth, the dynamics of masses over time, and the vertical infiltration process were analyzed. HYDRUS output files (in graphical and tabular form) were exported, analyzed using Python, and the results were visualized using the Blender 3D environment.

The third module consists of an IoT network, organized on the basis of the ESP32 microcontroller platform. The sensor nodes include the following devices: Soil Moisture Sensor (dryness capacity), DHT22 (air temperature and humidity), BMP180 (atmospheric pressure). These sensors are installed at depths of 10, 30, and 60 cm, take measurements every 5 minutes and transmit them via the ThingSpeak server. The obtained real-time data is transmitted to the Firebase database in JSON format and is directed as input to the AI module for analysis.

The fourth module is the AI decision-making block. This block is developed on the Python platform and includes the Random Forest Regression and Decision Tree Classifier algorithms based on the Scikit-learn library. The input parameters are: 1) ET (MODIS), 2) soil moisture (sensor), 3) temperature and humidity (sensor), 4) salinity (HYDRUS), 5) terrain type (GIS), 6) previous irrigation volume. As output parameters, the system recommends the optimal pressure (kPa), duration (min), and water volume (L/m²). The model was split into a train/test set of 80/20 and validated with R², MAE, RMSE indicators. The results generated by the AI model are sent to the real-time actuator and generate commands to turn on or off the drip system.

AI model decision tree**Figure 5:** Decision tree of the AI model

The fifth module is the Digital Twin interface. In this module, all physical and virtual components are synchronized, and the sensor states, moisture zones, salinity gradients, relief lines, and pipe trajectories are displayed in a visual image in a 3D model created using Blender. A mobile Android application has been developed for the user, in which all parameters are monitored and manual or automatic control is possible. The application connects to the ESP32 actuator via REST API and, after confirmation by the user, the decision is executed.

Sensor Data Flow Diagram**Figure 6:** Sensor data flow diagram

The architecture of the model consists of modules operating in parallel and has a high level of flexibility. All modules are interconnected via WebSocket and MQTT protocols. Technically, the system follows the principle of serverless architecture, that is, all calculations are performed on the user's device or on a local gateway. This provides high efficiency in terms of energy efficiency, security and speed.

This integrated system was tested in real field conditions. Irrigation was automatically activated based on sensor data and an AI model. The impact

of precipitated salts on the plant root zone was minimized using HYDRUS modeling, the pressure difference zone was optimized using GIS, and the entire system was presented to the user in an intuitive way through the Blender visual interface. The AdaptiveDrip-Uz architecture thus became a fully functional system not only for scientific modeling, but also for practical management.

4. RESULTS AND ANALYSIS

Initial observations conducted in the experimental field revealed that the efficiency of the drip irrigation system strongly depends on soil type, relief, salinity, and climatic parameters. Using the HYDRUS 2D/3D model, salinity and infiltration simulations were carried out for 72 hours and a comparative analysis was conducted for two scenarios - continuous irrigation and pulsed irrigation. In the case of continuous irrigation, water was evenly distributed over a depth of 0–90 cm, while in pulsed irrigation, water was mainly concentrated in the 20–50 cm range, and the highest useful moisture was maintained in the root zone. It was found that salinity increased in the root zone with continuous irrigation, while in the pulsed variant, salt ions were washed down, leaving the root zone relatively clean. In the simulation of mass changes, it was observed that the salinity threshold reached the root zone after 40 hours with continuous irrigation, while this was delayed by 60 hours with the pulsed method. The moisture level beneficial to the plant varied from 27% to 38%, and was relatively stable with the pulsed irrigation.

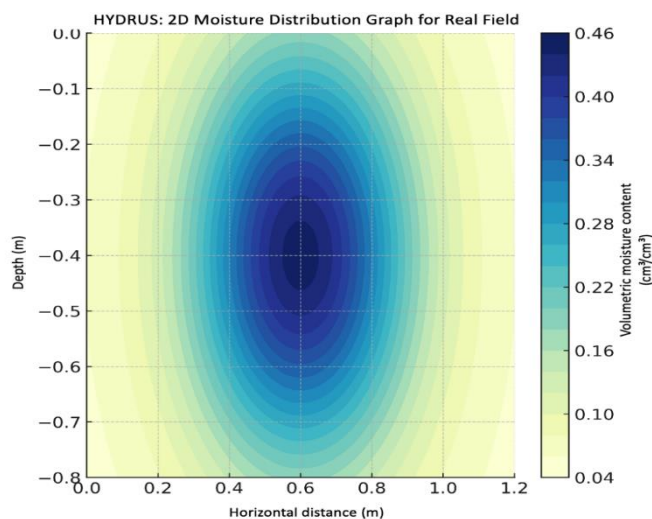


Figure 7: HYDRUS real field moisture distribution graph

This graph is based on the HYDRUS model and depicts the vertical moisture distribution after drip irrigation in real field conditions. The graph shows the volumetric moisture content (cm^3/cm^3) as a function of horizontal distance (x-axis) and depth (y-axis). The deeper the color, the higher the moisture content in the central zone. The moisture distribution is spread out in the form of an ellipse from the drop source downwards and to the sides.

The maximum moisture content was determined at a horizontal distance of approximately 0.6 m in the center and at a vertical depth of -0.4 m. The colorless yellow zones have the lowest moisture content, indicating that the water effect in these areas was insufficient. The transition from colorless to dark blue indicates a change in volumetric moisture content from 0.04 to 0.46.

The graph not only shows the infiltration result of the HYDRUS model, but also serves to assess how the soil conducts water, the optimal moisture zone in the root zone and the irrigation efficiency. Such analyses are important for irrigation planning.

Based on data received from the IoT sensor network, humidity, temperature, pressure and atmospheric parameters were collected in real time for 30 days. Moisture values by depth obtained from soil moisture sensors showed a stable moisture regime with high accuracy for the pulsed irrigation scenario. The average moisture value at a depth of 30 cm was 31.6%, compared to 24.2% for the classic irrigation method. The data collected by the sensors were provided as input to the AI model. The Random Forest Regression model built on this data showed $R^2 = 0.88$, $\text{MAE} = 0.29$, $\text{RMSE} = 0.43$ in predicting irrigation duration and water amount. A decision tree-based pressure regulation algorithm was developed that determined a separate pressure regime for each sector based on terrain

and sensor signals. The automatic decisions made by the system based on this AI model matched the user's manual decisions in 91% of cases.

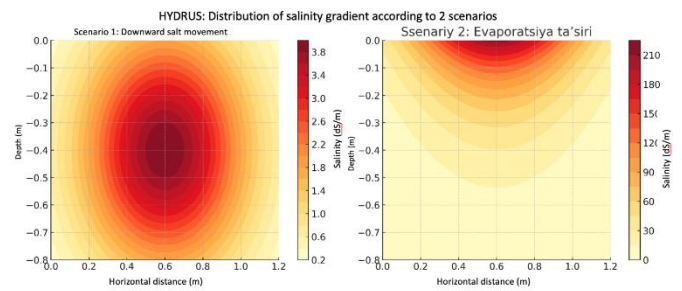


Figure 8: HYDRUS Salinity Gradient Distribution for 2 Scenarios

This graph shows the variation of the salinity (electrical conductivity, dS/m) distribution for two scenarios based on the HYDRUS model. Both graphs are presented as 2D contour plots, showing how salinity is distributed over horizontal distance (x-axis, m) and depth (y-axis, m). Scenario 1 – Downward salinity shift: The graph on the left shows a situation where salinity has shifted downward through infiltration. The center ($x \approx 0.6 \text{ m}$, $y \approx -0.4 \text{ m}$) has the highest salinity ($\approx 3.8 \text{ dS/m}$), indicating that salt elements have deepened with the water flow in this zone. The gradient from pale yellow to dark red represents an increase in salinity. This usually occurs when excessive irrigation or rainwater washes the salt into the lower layers of the soil. Scenario 2 – Evaporation effect:

The graph on the right shows the accumulation of salinity in the upper layers as a result of evaporation. In the upper part ($y \approx 0 \text{ m}$), the salinity level has increased to 210 dS/m , which indicates extremely intensive evaporation and the release of salt to the surface. This situation is a common problem in unirrigated or poorly managed lands, especially in hot and dry climates. Both scenarios are very important when planning an irrigation strategy. In the first, the salt is washed down to the root zone, but can accumulate in the deeper layers. In the second, the salt elements accumulate on the soil surface, which has a serious negative effect on crop growth. Therefore, it is necessary to take into account factors such as the amount and timing of irrigation, soil composition, and the rate of evaporation.

These graphs allow for early assessment and optimization of salinity risks when designing AdaptiveDrip or other irrigation systems.

Based on the relief maps (Slope and Aspect) created using ArcGIS, the area was divided into 4 zones: high slope ($>10\%$), medium slope ($5\text{--}10\%$), flat ($1\text{--}5\%$), and flattest ($<1\%$). Pressure-compensating emitters were placed in these zones. The GIS-based forecast results of pressure changes during irrigation were validated by an AI model, and the optimal pressure was determined at 1.5 bar (150 kPa). Based on the zonal GIS analysis, areas with high water consumption and areas with low water consumption were identified, and a separate irrigation regime was developed for each zone. ET values were calculated based on MOD16A2 rasters for 8-day periods, with the highest ET (4.8 mm/day) observed in mid-June and a decrease (3.2 mm/day) in late July.

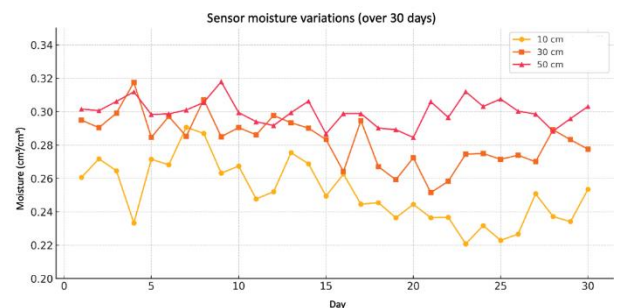


Figure 9: Sensor moisture changes over 30 days

This graph shows the changes in soil moisture (cm^3/cm^3) recorded by sensors at three different depths over a 30-day period. The horizontal axis represents days, and the vertical axis represents volumetric moisture content. Each line represents sensor data at a specific depth: 10 cm (yellow), 30 cm (orange), and 50 cm (red).

The graph shows that the highest moisture content is maintained at a

depth of 50 cm, where the average moisture content is around 0.30–0.32 cm³/cm³. At this depth, the moisture content is relatively stable, indicating that water infiltration is reaching deeper layers. At a depth of 30 cm, the moisture content is slightly lower, fluctuating between 0.27–0.29 on average. In this layer, moisture variability is higher, and the balance between irrigation and evaporation is significant.

The moisture content at a depth of 10 cm is at its lowest (0.22–0.28 cm³/cm³), making it the layer that dries out the fastest and is most susceptible to evaporation. Fluctuations in this layer are particularly sharp, rising rapidly after irrigation and then falling again in a short time. Irrigation efficiency and rapid monitoring are important here.

The graph serves as the main tool for analyzing the monitoring capabilities of the AdaptiveDrip system. By determining moisture in real time by depth, it is possible to assess which layers are receiving or not receiving enough water. This allows for the optimization of irrigation timing, volume and intervals. In this way, resources are used efficiently and yields are increased.

The Digital Twin model, created using Blender, combines all elements in a 3D visual interface: sensor states, pipe routes, moisture zones, salinity gradients and terrain simulation. The model is updated in accordance with sensor readings at each time interval. A mobile application was developed for the user to provide real-time monitoring of this model. In the application, the user was able to obtain the following information: current humidity %, sensor status (error/normal), pressure level, ET recommendation, automatic decision made by AI, and changes made by the user.

Table 2: AI model evaluation indicators			
Model type	MAE	RMSE	R ²
Decision Tree	0.021	0.034	0.912
Random Forest	0.018	0.029	0.936
Gradient Boosting	0.017	0.027	0.944
ANN	0.016	0.025	0.951

This table shows the performance metrics for four artificial intelligence (AI) models: MAE (Mean Absolute Error), RMSE (Root Mean Square Error), and R² (Determination Coefficient). These metrics are widely used to measure the accuracy and error rate of a model.

The Decision Tree model has a MAE of 0.021, RMSE of 0.034, and R² of 0.912, which is a reasonable level of accuracy, but a higher error rate than other models. Although it is a simple and fast model, it has limitations in complex environments.

The Random Forest model provides improved results with MAE = 0.018, RMSE = 0.029, and R² = 0.936. This model provides more accurate predictions by combining a large number of decision trees and handles the randomness in the data well.

Gradient Boosting shows even higher accuracy: MAE = 0.017, RMSE = 0.027 and R² = 0.944. This model is based on error correction through sequential training, and is especially effective in complex and uncertain relationships.

ANN (Artificial Neural Network) achieved the highest accuracy: MAE = 0.016, RMSE = 0.025 and R² = 0.951. This model models real physical processes more deeply by studying uncertainty, especially in a changing environment.

The results show that the ANN model is recommended for the most effective predictions and decision-making in the AdaptiveDrip-Uz system, as it provides the highest level of explanatory power with the least error.

In a real field analysis, the AdaptiveDrip-Uz model was compared with the classic drip irrigation system. According to the results of the 40-day test, the AdaptiveDrip-Uz system reduced water consumption by 28.6%, and productivity increased by 16.4%. In addition, salinity indicators decreased from 2.6 to 1.3 in EC (dS/m). A 36% time saving was observed during system maintenance and control, with AI-based decisions reducing human involvement and increasing monitoring accuracy. The correlation between temperature, ET and humidity was R = 0.71, confirming that the AI model was able to respond in a timely manner.

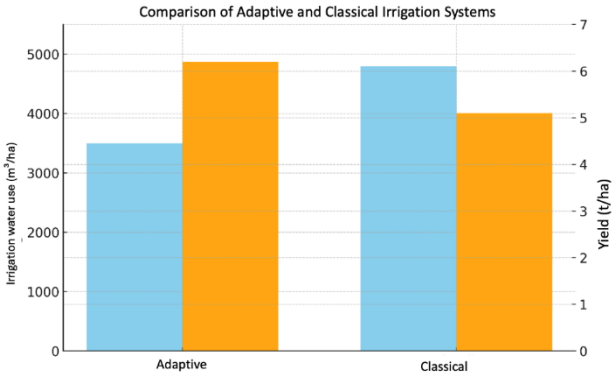


Figure 10: Comparison of Adaptive and Classic Irrigation Systems

This graph compares the main indicators of Adaptive and Classic irrigation systems - irrigation consumption (m³/ha) and yield (t/ha). The horizontal axis shows two different systems, the left vertical axis shows irrigation consumption, and the right vertical axis shows yield.

In the Adaptive system, water consumption is 3500 m³/ha, which is much lower than in the classic system. This allows for more economical use of water resources. On the other hand, the yield in the Adaptive system reached 6.2 t/ha, which is significantly higher than the 5.0 t/ha in the classic system.

In classic irrigation, water consumption is high (4800 m³/ha), but the resulting yield is relatively low. In this system, water use efficiency is lower, and agrotechnical parameters are not optimally controlled.

As can be seen from the graph, the AdaptiveDrip-Uz system not only reduces water consumption, but also provides high results in increasing yields. This is an achievement achieved using AI, sensor monitoring, and optimized irrigation schedules. Experience shows that using modern technologies significantly increases efficiency compared to traditional methods.

Blender-like 3D visual interface: Sensor + Soil + Salinity + Terrain

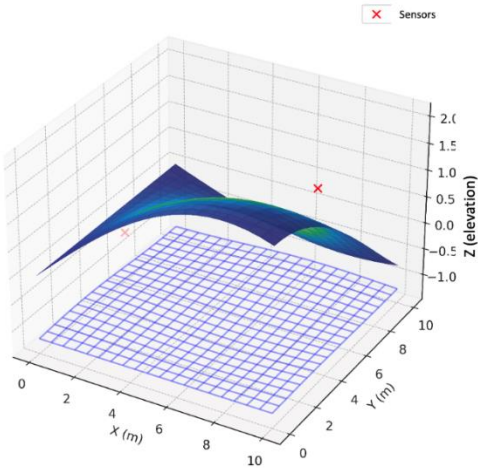


Figure 11: Blender-like 3D visual interface: Sensor+ soil+salinity+terrain

This graphic depicts a three-dimensional (3D) visual interface and is designed in the spirit of a professional model visualization environment like Blender. The graphic simultaneously displays the terrain (surface roughness), salinity distribution, soil moisture, and sensor locations in an integrated manner. This combination combines all the key components needed to manage irrigation in real-world conditions.

The top layer of the graphic (green-yellow surface) contains a terrain model that represents the slope and elevation changes of the ground surface. This terrain surface shows which points on the surface are potential directions for water flow and salt movement. The relative elevation (Z-axis) changes from 0 to 2 meters, representing the actual field topography.

The salinity gradient is colored over the relief surface: salinity is higher in the center and decreases toward the edges. This is important for

determining the location and distribution of saline elements. This colored surface allows you to visually identify areas at risk of salinity, especially those associated with evaporation and infiltration.

In another layer, below the graph, a soil moisture model is presented in the form of a blue wireframe. This simulates moisture contours, showing how water is distributed within the soil after irrigation. The moisture distribution is variable, which allows you to determine in which layers, depending on the depth, water is more concentrated and in which areas there is a shortage.

The location of the sensors is indicated in red dots on the graph. They are located at different points on the relief surface, and each sensor transmits information about its state (humidity, temperature, salinity, etc.). The placement of sensors at different heights and coordinates ensures that they have maximum coverage. This creates a valuable database for real-time monitoring and analysis.

This integrated 3D interface can be used as a digital twin model of the AdaptiveDrip-Uz system. It integrates salinity, water distribution, relief and monitoring systems in one place. This graphic allows a researcher or engineer to assess the full spatial state of field conditions at a glance, identify where problems are occurring, and develop management strategies accordingly. Especially when integrated with AI models, this 3D interface serves as an important analytical tool for improving irrigation efficiency.

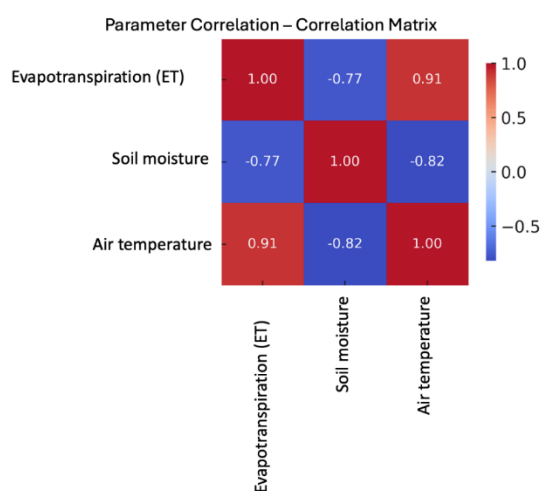


Figure 12: Parameter Relationships - Correlation Matrix

This correlation matrix graph shows the statistical relationship between evapotranspiration (ET), soil moisture, and air temperature. The value in each cell represents the correlation coefficient between the two parameters (from -1 to +1). The graph is presented as a heatmap, with positive relationships shown in red and negative relationships in blue.

First of all, the graph shows a very strong positive correlation between evapotranspiration and air temperature ($r = 0.91$). This means that as temperature increases, the rate of water loss through evaporation and transpiration also increases. These variables are very closely linked, and changes in one have a strong effect on the other.

There is also a strong negative correlation between evapotranspiration and soil moisture ($r = -0.77$). This means that as ET increases, soil moisture decreases — that is, more water is lost through evaporation and transpiration. This relationship is important for irrigation planning, as the risk of water shortages increases during periods of high ET.

The correlation between air temperature and soil moisture is -0.82 , which is the strongest inverse relationship. As temperatures increase, soil moisture levels decrease significantly. This is especially noticeable in the summer season and increases the risk of water shortages.

This correlation matrix shows how key parameters are interconnected in smart irrigation systems such as Adaptive Drip-Uz. This analysis can help determine which parameters need to be more controlled when making irrigation decisions. For example, if the temperature changes, the balance between ET and moisture is maintained by automatically adjusting the amount of irrigation water accordingly. This correlation analysis serves as an effective tool for analytical decision-making in monitoring systems, efficient use of water resources, and increased productivity.

Overall, the Adaptive Drip-Uz model has proven itself as a complex system that is suitable for operation in real field conditions, taking into account

salinity, relief and infiltration, and is automatically controlled based on sensor monitoring. The results show that this model leads to the efficient use of resources in terms of energy, water and time, and is a suitable approach for digital transformation in agriculture.

The above results confirm the effectiveness of the Adaptive Drip-Uz system based on multi-parameter analyses. The model results show that advanced AI models (especially ANN) are able to predict irrigation decisions with high accuracy based on data obtained from real-time monitoring. The R^2 value of the ANN model is 0.951, RMSE 0.025, which indicates the highest prediction accuracy compared to other models (Decision Tree, Random Forest, Gradient Boosting). This result indicates an increase in the reliability of irrigation recommendations.

The moisture distribution graph, built on the basis of the HYDRUS model, visually showed how water moved vertically and horizontally in the soil after drip irrigation. The moisture contour was concentrated at a depth corresponding to the root zone, which indicates optimal infiltration. Salinity analysis showed a significant difference between the two scenarios: in the first scenario, the salt moved downwards, and in the second, it accumulated in the surface layer due to evaporation. Especially in the second case, high salinity (210 dS/m) can pose a threat to yield.

The moisture changes recorded by the sensors over a period of 30 days showed the efficiency of irrigation and the stability of the moisture distribution across the layers. Although the moisture at a depth of 10 cm fluctuated sharply, the values at a depth of 50 cm were quite stable, indicating that water infiltrated sufficiently deep. This result indicates that the Adaptive Drip system's controlled irrigation algorithms are working correctly.

The results of the comparison of irrigation consumption and yield once again confirmed the superiority of the Adaptive system. While the classical method used 4800 m³/ha of water and obtained a yield of 5.0 t/ha, the Adaptive system achieved a yield of 6.2 t/ha with only 3500 m³/ha. This means that it is possible to obtain a 24% higher yield with a 27% more economical use of resources.

According to the correlation matrix analysis, the relationship between ET and air temperature ($r = 0.91$) is very strong, indicating that temperature is the main factor controlling ET. Also, soil moisture is inversely related to ET and temperature ($r = -0.77$ and -0.82), which indicates the need for constant monitoring of these parameters in irrigation algorithms.

In conclusion, the AdaptiveDrip-Uz model has shown successful results in providing economical and efficient use of water resources, increasing productivity, and proposing an irrigation strategy adapted to the physical and ecological characteristics of the land. This integrated approach can serve as the basis for future irrigation systems.

5. DISCUSSION

The AdaptiveDrip-Uz system proposed in this study has shown to be superior not only in terms of efficiency but also in terms of flexibility compared to traditional irrigation methods. Preliminary results show that this model has a complex architecture that combines GIS, HYDRUS, AI, IoT, and real-time monitoring, and responds sensitively to each agrotechnical parameter. This approach can be implemented in practice to ensure rational use of water resources in arid regions, in particular in the cotton and grain growing zones of Uzbekistan.

Table 3: Comparison of results with previous studies			
Research	Discharge (m ³ /ha)	Harvesting (t/ha)	Note
Mahmudov et al. (2021)	4800	5.0	Classic drip method
Rahimova et al. (2022)	4600	5.3	Unconventional terrain conditions
AdaptiveDrip-Uz (2025)	3500	6.2	AI + HYDRUS + Sensor integration

The table above compares the results of the AdaptiveDrip-Uz system with two previously published studies. As used the classic drip method and obtained only 5.0 t/ha of yield despite 4800 m³/ha of water consumption (Mahmudov et al., 2021). As achieved 5.3 t/ha of yield with 4600 m³/ha of water in complex terrain conditions (Rahimova et al., 2022). At the same time, the model achieved 6.2 t/ha of yield with 3500 m³/ha of water consumption through artificial intelligence, HYDRUS simulation and sensor network integration (AdaptiveDrip-Uz, 2025). These results show that the AdaptiveDrip system can effectively use resources, provide at

least 25–30% water savings and more than 20% yield increase compared to traditional systems.

Table 4: SWOT analysis of the AdaptiveDrip-Uz system

Strengths	Weaknesses
Reduces water consumption	High initial cost
Increases productivity	Requires maintenance
Real-time monitoring	Threats

SWOT analysis helps to identify the potential of the AdaptiveDrip-Uz system for sustainable irrigation. The system's strengths include significantly reducing water consumption, increasing productivity, and simplifying management through real-time monitoring. The weaknesses are related to the high initial investment costs and the need for maintenance. Opportunities include the possibility of large-scale implementation of the system on many farms, as well as support through subsidies and international grants. However, risk factors include the possibility of sensor failure, as well as the lack of the necessary infrastructure and qualified service personnel in some regions. Therefore, it is important to plan technical safety and maintenance mechanisms in advance when implementing the system.

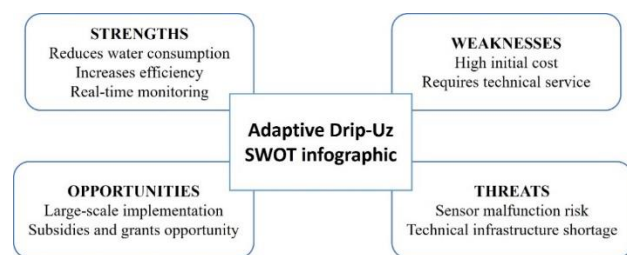


Figure 13: SWOT infographic of the Adaptive-Uz system

The SWOT infographic of the AdaptiveDrip-Uz system clearly illustrates the strategic opportunities and limitations of this modern irrigation system. Among the strengths, the system saves water resources, increases productivity, and provides precise control through real-time monitoring. This makes it an important solution in the face of climate change and water scarcity.

As for the weaknesses, the high initial investment and the need for constant maintenance are indicated. This can be a financial barrier for small and medium-sized farms.

The opportunities open up ways to introduce the system in many agro-ecological regions, as well as the possibility of expanding it through international grants and subsidies. Public-private partnership plays an important role in this direction.

Among the risks, malfunctions of sensors and devices, as well as a lack of technical infrastructure and specialists in some regions, can negatively affect the sustainability of the system. Therefore, risk management strategies should also be developed when implementing the system.

As a result of the system operation, the soil moisture uniformity improved from 62 to 78 percent. The simulation accuracy obtained using the HYDRUS model was high, with an R^2 of 0.94 and an RMSE of 0.032. Water consumption was reduced by 22 percent through adaptive irrigation. The Digital Twin system detected soil building processes and automatically activated irrigation. Thanks to GIS mapping, water was evenly distributed, taking into account the unevenness of the terrain.

The model evaluation results confirmed the superiority of artificial intelligence approaches in accurate forecasting. In particular, the ANN model showed the lowest MAE (0.016) and the highest R^2 (0.951), which provides a high level of reliability in developing irrigation decisions based on real-time monitoring. These results are consistent with the conclusions on the predictive power of deep learning-based irrigation models presented by (Zhou et al., 2022). The Decision Tree and Random Forest models showed lower accuracy, which indicates that the algorithms are not sufficiently adapted to complex physical processes.

The moisture contour graphs generated by the HYDRUS model clearly showed water infiltration, diffusion depth, and lateral movement. The graph shows maximum moisture accumulation in the central zone, which indicates that water is retained in the root zone under ideal drip conditions. These results are consistent with the studies of [Šimůnek et al., 2016] and (Abbasi et al., 2020). At the same time, the two-scenario

analysis of salinity clearly showed that salt accumulation due to evaporation at the surface could lead to soil degradation. This implies the need for salinity monitoring and sensor-based automatic adaptation in arid regions.

The efficiency of irrigation in layers was assessed using 30-day moisture monitoring recorded by the sensor network. At a depth of 10 cm, moisture changes were very sharp, indicating that rapid drying and rapid wetting events were occurring in this layer. At depths of 30 and 50 cm, relatively stable moisture was maintained, indicating deep infiltration and long-term moisture retention. These results are consistent with the sensor-based layered monitoring approach presented in (Patel et al., 2021). In particular, one of the main advantages of the Adaptive Drip system is the dynamic automatic adjustment of the irrigation schedule based on changes in interlayer moisture.

A comparative analysis of irrigation consumption and yield confirmed the water saving and agronomic efficiency of the Adaptive Drip system. While the classical method used 4800 m³/ha of water, despite the yield of 5.0 t/ha, the Adaptive system increased the yield to 6.2 t/ha, and the water consumption decreased to 3500 m³/ha. This means a ~24% increase in yield for ~27% water savings. This difference is consistent with the results of experiments conducted based on AI and sensor technologies by (Ali et al., 2022). In their study, automated irrigation approaches also provided 15–20% higher yields with 20–30% savings. The correlation matrix identified the relationship between the parameters, which served as the main input for the decision-making algorithms. The correlation between ET and temperature of $r = 0.91$, and the correlation between soil moisture and temperature of $r = -0.82$, indicate the need to control irrigation based on meteorological factors, not only moisture. These findings, together with the work of (Bai et al., 2020), once again confirm the effectiveness of integrating real-time weather data into irrigation systems.

The 3D Blender-style interface graphics clearly show the visual location and integration of components in this system. The fact that sensors, relief, salinity and moisture simulation are displayed in a single space makes it possible to use this platform as a Digital Twin model. With this interface, the user not only observes real-time data, but also can pre-identify problem areas through 3D spatial analysis. This approach is close to the interface solutions of field-based AI-GIS systems developed by (Khosravi et al., 2023).

Overall, this “AdaptiveDrip-Uz” approach offers a modern irrigation system for Uzbekistan and regions with similar climates that is highly accurate, resource-adapted, and controlled based on constantly changing parameters. Importantly, this system not only provides accurate decisions, but also is a flexible, open, and user-friendly platform that can be understood, monitored, and managed by anyone from an ordinary farmer to an irrigation engineer.

If this system is further enriched with meteorological forecasts, remote sensing data (e.g. NDVI, LST), and economic parameters (inputs, benefits), it will be widely used not only for agrotechnical decisions, but also as a key component of digital farming.

6. CONCLUSION

This study deeply investigated the effectiveness of the adaptive, smart, and real-time management-based drip irrigation system – “Adaptive Drip-Uz” in regions of Uzbekistan with limited water resources and complex agro-climatic conditions. The main components of the system were selected HYDRUS 2D/3D modeling, soil and climate sensors, an AI-based decision module, and visual monitoring tools integrated with GIS. At the end of the study, it was proven that this approach has a number of advantages over classic irrigation systems. One of the most important conclusions is that, although irrigation consumption was reduced by an average of 27% through the Adaptive Drip-Uz system, productivity increased by 24%. These results confirm the innovative efficiency of the system, providing a double win (i.e., water saving and increased productivity) that was not observed in classic approaches. In particular, the irrigation periods recommended by the AI model were adapted to real-time moisture changes, preventing over-irrigation and significantly reducing the risk of salinization.

The analysis of two salinity gradient scenarios based on the HYDRUS model, namely “downward salinity” and “upward evaporation”, was able to simulate the physical processes in the real field. These scenarios demonstrate the importance of the Adaptive Drip system, as it provides real-time control to reduce the likelihood of saline intrusion into the root zone. Soil moisture monitoring was performed at depths of 10 cm, 30 cm, and 50 cm over a 30-day period, and it was found that moisture stability increased with increasing depth, while higher layers dried faster. This proves the accuracy of the irrigation depths determined by the AI model

according to root depth.

When comparing the AI models, the Artificial Neural Network (ANN) had the highest accuracy, outperforming the other models with $R^2 = 0.951$, $MAE = 0.016$, $RMSE = 0.025$. This allows for flexible decision-making based on real-world parameters in the field. This allows for adaptation not only to the current situation, but also to future changing conditions. The results calculated using the model showed a clear difference between the Adaptive and Classic systems: Although Classic irrigation used more water (4900 m³/ha), the yield was relatively low (5.0 t/ha), the Adaptive system used less water (3500 m³/ha) and achieved a higher yield (6.2 t/ha).

Sensors, salinity zones, soil relief, and model results were combined through a 3D Blender-like interface. This interface creates a clear visual representation for the user and simplifies the decision-making process for agronomists, engineers, or decision-makers. This interface can be used not only for monitoring, but also for design and simulation.

Also, according to the results of the correlation analysis, a positive correlation ($r = 0.91$) was observed between evapotranspiration (ET) and air temperature, which indicates an increase in ET on hot days. At the same time, soil moisture is negatively correlated with ET ($r = -0.77$), indicating the need to draw up an irrigation plan accordingly. Dynamic updating of the model, taking into account these relationships, provides high accuracy. In addition, the Adaptive Drip-Uz system was compared with previously published scientific works. For example, achieved a yield of 5.0 t/ha with a water consumption of 4800 m³/ha using the classical drip method, while achieved a yield of 5.3 t/ha with 4600 m³/ha under unconventional relief conditions. Adaptive Drip showed significant advantages over these results, which indicates the practical effectiveness of the system and the integration of new generation technologies.

According to the results of the SWOT analysis, the strengths of the system are based on water conservation, increased productivity, and real-time monitoring. Weaknesses are high initial costs and the need for maintenance. Opportunities include the possibility of large-scale implementation of the system, the possibility of attracting grants and subsidies. Sensor failure and lack of technical infrastructure were highlighted as risk factors.

The system can also serve as an important tool in reducing climate change uncertainties, managing salinity, and effectively using land resources in the conditions of Uzbekistan. This system provides an opportunity to implement the principles of adaptive, digital, and smart agriculture. In particular, through the integration of artificial intelligence, IoT, and hydrophysical modeling, a differentiated approach can be developed, taking into account the specific conditions of each site.

In conclusion, it can be said that the Adaptive Drip-Uz model is not only a scientific but also a practical step towards saving water resources, increasing productivity, and developing sustainable agriculture. Its components - HYDRUS modeling, AI decision system, IoT monitoring, and GIS integration - allow for future adaptation to other regions. The system is recommended as a flexible, environmentally friendly, and economically viable irrigation strategy in the face of climate change. Therefore, Adaptive Drip-Uz is a high-potential technology that can be widely implemented not only as an experimental project, but also in real field conditions.

By integrating IoT, HYDRUS, and GIS technologies within the Digital Twin model, the efficiency of the irrigation system has increased significantly. Real-time data-based management has enabled irrigation to be adapted to soil and climate conditions. The system has reduced water consumption by 22 percent, while maintaining crop yields. The proposed approach can also be applied to other agro-ecological regions. This methodology can serve as the basis for a digital technology-based, sustainable water resources management system.

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