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Improvement of Irrigation Water Management Using Simulation Models And Artificial Intelligence Under Dry Environment Conditions In Egypt: A Review

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Abstract

Agriculture is facing major challenges such as inefficient irrigation systems, climate change, groundwater intensity, food shortages as well as reuse of food and water wastes, and much more. The acceptance of different cognitive solutions has a significant impact on the fate of cultivating. With a growing population, there is a pressing need to provide more food and agricultural crops, which necessitates the supply of sufficient water. In agriculture and other human activities, water is still the most important factor.Traditional irrigation water management methods are insufficient to face the rising demand. Artificial intelligence and simulation models are two new technologies that can help with irrigation and water conservation. Farmers will benefit from the technology because it will help them achieve higher yields and a more consistent seasonal crop. Artificial intelligence is useful to be used in irrigation practice and to predict weather and other agricultural conditions. Most of the farmers' concerns would be alleviated by accurate projection or prediction using AI technology. AI-powered sensors are extremely useful for extracting essential agricultural data. The information will be helpful in improving efficiency of irrigation application.Those designing the next generation of agricultural systems models, data, and information systems should embrace new technologies and knowledge. Smart phones and networking, remote sensing, open source software tools, and cloud computing as a way of allowing wide access to powerful tools are all examples of modern technology.

Key words: Artificial intelligence, irrigation water management, simulation models, smart irrigation

Introduction

Agriculture is critical to any country's economic development. With the rise in population, regular changes in climatic conditions, and scarce resources, meeting the current population's food needs has become a difficult challenge. Irrigation is playing a master role in agriculture practices especially under a scarcity of water [1]. Egyptian agriculture is mainly dependent on irrigation from the Nile River. Due to the limited and constant amount of water from the River Nile, which is 55.5 billion m3 per year, and the dramatic increase in the population, the annual share of water per capita is decreasing. This in turn led to water scarcity. Moreover, agriculture is the main consumer of water resources in Egypt with its primary source from the Nile, and where the upstream countries are planning to reduce Egypt's fixed annual income share, it is imperative that the Egyptian agricultural policy must work in all directions and by all means to rationalize water use in all sectors and to raise the crops water use efficiency in the agricultural sector [2] Water scarcity is a very serious problem facing food production in dry Egypt. It is important to save irrigation water and reduce consumption by modernizing and developing innovative and sustainable

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technologies [3,4]. In dry Egypt, the sector concerned with the agricultural process faces a difficult challenge, which is how and how to increase crop production through irrigation with less water volume, which is currently known to increase the water productivity of crops. [5]. Water resources in Egypt suffer from severe shortages and scarcity, and this suffering is gradually increasing with the increase in the population growth rate. In addition to the increasing competition for limited water resource sources, which led to most of the new irrigation technologies competing to increase water productivity and improve and increase crop productivity and quality [6]. The main goal of all those working in the field of water management is to increase the water productivity of crops, as it is an important and necessary goal in order to increase the increasing demand for food resulting from the turbulent rise in population growth [7].

It was also emphasized that increasing the productivity of the unit of water needed to irrigate agricultural crops in Egypt is a very important issue, due to water scarcity, limited sources, and low annual rainfall [8]. The application of different techniques for new irrigation systems and methods and related sustainable techniques is one of the important concepts that must be adopted, followed and applied in arid and semi-arid regions as it exists in the Arab Republic of Egypt to provide a large part of irrigation water [9]. The biggest and most important challenge facing the environment is the agricultural sector, which is to produce and grow more crops with less water, which can be achieved by using all available technologies to increase the water productivity of crops. (WP) [10].

Precision and modern irrigation have emerged as a cutting-edge method for addressing emerging agricultural sustainability issues.Without the aid of technology, the current modern irrigation system is unable to predict the actual amount of water needed for crops. It may result in either under or over-irrigation. The soil moisture will be affected by irrigation, and the crop will be lost. Crop diseases and clogging are caused by excessive irrigation. It will have an effect on yield performance.To avoid these issues, it was also necessary to improve the current modern irrigation system. The automatic irrigation system, smart irrigation, was developed using a variety of technologies [11].

The irrigation water distribution system is primarily run by hand, which makes accurate measurement of channel and field conveyance losses difficult. As a result, making agricultural water use more effective in the fields and increasing operational precision by the use of modern irrigation systems and artificial intelligence (AI) will ensure adequate irrigation and yield during droughts [12].

In the field of agriculture, (AI) is a new technology. Agriculture has been elevated to a new level according to AI-based equipment and machines. Crop quality has increased as a result of this technology, as has real-time tracking, harvesting, processing, and marketing [13].

The use of agricultural robots and drones in automated systems has made a significant contribution to the agro-based field. A variety of high-tech computer-based systems have been developed to evaluate various important parameters such as irrigation, weed detection, yield detection, crop quality [14].

Such technologies as simulation models and artificial intelligence (image recognition and perception, artificial neural network, deep learning and machine learning) aid in the effective use of water, water efficiency, and the improvement of irrigation water management and product quality and quantity.

SIMULATION MODELS

Simulation models are computer programmes that simulate how crops grow and develop. Crop yield, maturity date, fertiliser performance, and other aspects of crop production are predicted using weather, soil, irrigation water requirements and crop management data. The crop models' estimates are focused on what is currently known about the physics, physiology, and ecology of crop responses to the environment.

Crop models are based on more modern methods, whose fundamentals emerged from the 1950s to the 1960s. Hydrologic models are based on studies that began in the nineteenth century [15, 16].

The modelling approaches of soil-water movement (e.g. penetration, capillary forces, drainage processes) were developed after Darcy's equation and Beer-Lambert law. The variety of methods used to simulate the function of water varied across models and processes, which is partially due to the historical context of the models as shown in Figure (1)

Chronological map of modelling approaches [17].

Crop simulation models depict the stage-by-stage growth of a crop in relation to climate and other factors. Crop simulation models assist farmers in making informed decisions in order to increase crop yield. Crop models simply predict the growth stages of crops over time. Crop supervision, such as irrigation, fertilisation, planting, and disease protection, is usually included in the assessment of crop growth and yield. Crop models may be classified as descriptive, statistical, deterministic, stochastic, dynamical, or explanatory model [18].

At the design, planning, and operations levels, simulation modelling techniques remain a valuable tool for addressing a variety of engineering problems (such as irrigation management). As a result, the use of simulation models in irrigation water management decreases water and energy usage, resulting in improved resource utilisation performance.

While hydrologic models are important in natural resource management, the majority of crop models were developed and tested in controlled situations. On the other hand, these crop models are increasingly being used for areas larger than a single sector. Inadequate representation of spatial uncertainty at a larger scale causes significant errors in model predictions. However, the lack of data for calibration and validation makes their use difficult. As a result, it's critical to use the regionalization with physical similarity approach to calibrate, and validate models [19, 20]. Simulation testing is easier and less expensive than field experiments, which is one of the benefits of using simulation models. The second benefit of using models is that they have a lot more detail than experiments.

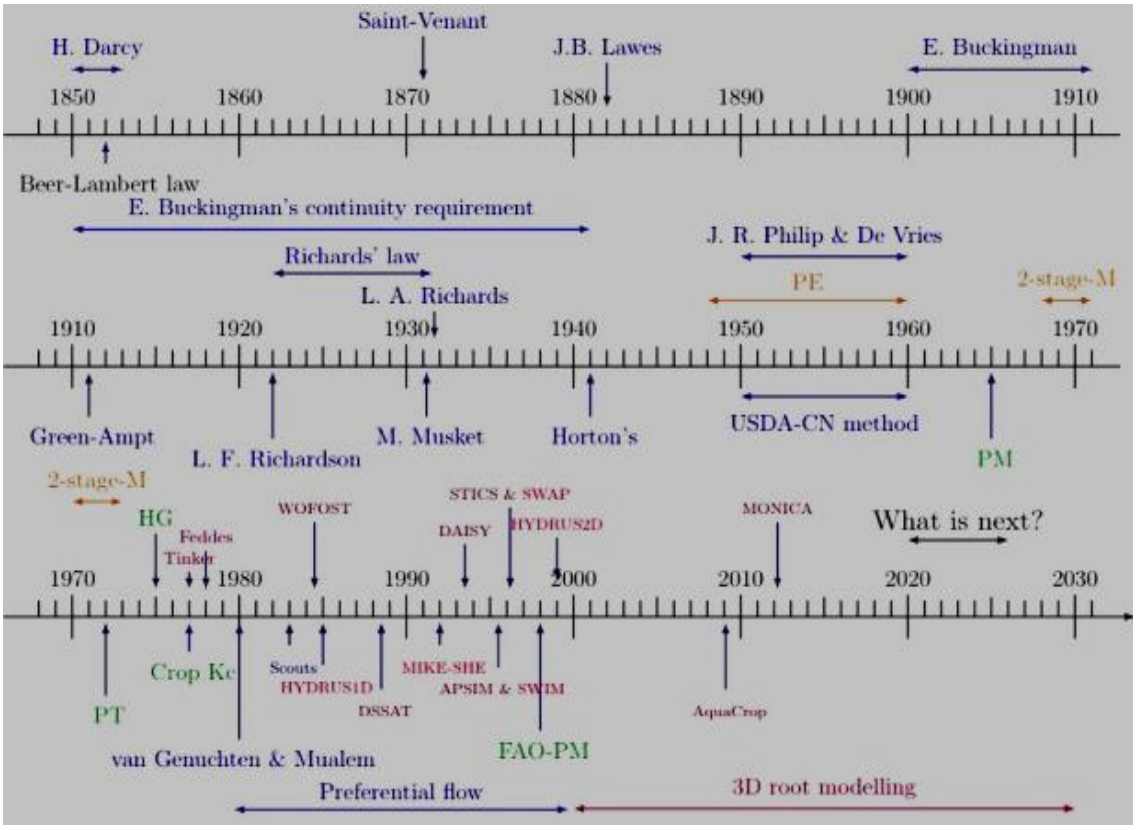

Figure (1): Historical context of the models [17]

Agricultural simulation models that are properly calibrated and validated provide a systems approach and a fast alternative method for developing and testing agronomic practises that can take advantage of technical advancements in limited irrigation agriculture.

To simulate the furrow irrigation method, Holzapfel et al., [21] developed and used volume-balance irrigation models with a recession step and analyses the relationship between furrow irrigation variables and irrigation efficiency parameters, crop yield, and deep percolation as a basis for furrow irrigation design and management. According to the study's findings, the model may be used to develop effective irrigation procedures and to avoid contamination.

Surface irrigation simulation models are helpful during the design and management stages of surface irrigation systems. Simulation models aid in the optimization of surface irrigation variables such as field slope, field length, and design flow rate when used for irrigation design. That is, the models will assist the designer in determining the best values for these variables to achieve the best results. This is most useful for newly formed fields or when switching from another application process to a surface system. Once the system is up and running, changing these variables (particularly field slope and length) is difficult or costly [22].

Many simulation models, such as the SpacePro model for selecting nozzle size and spacing for a given application, the SIRIAS model for sprinkler droplet simulation, and the TRAVGUN model for sprinkler application depth, have proven to be very effective in the design and management of pressurised irrigation systems [23].

Several simulation models have been developed to study the flow processes involved during an irrigation event in basin irrigation to improve the design and operation of thebasin layouts. The absolute hydrodynamic Saint–Venant equations or the simplified zero-inertia approximation “neglecting inertial terms” was used as governing equations for the simulation models [24, 25].

El-Shafie et al., [26] developed and tested GPIMOD gated pipe irrigation simulation model, concluding that it is a useful tool for predicting water distribution uniformity along gated pipes.

Razzaghi et al. and Mbangiwa et al. [27,28] stated that AquaCrop is a model that is dominating the usage of water in great amount, it is a model for predicting crop water efficiency established by FAO and can be used extensively in any place and time by regularizing a water-productivity parameter for climate (evaporative demand and concentration of atmospheric carbon-dioxide). A number of studies verified that AquaCrop gave a precise forecast ofirrigation requirements, crop biomass and harvest. Also, the model is relevant to apply in studying scenarios of climate change and it is effect on irrigation.

Using various furrow lengths and slopes, Dewedar et al., [29] validated the WinSRFR simulation model as a tool for predicting furrow irrigation performance. The statistical indicators for comparing calculated and simulated advance time, recession time, and DU were adequate and highly satisfactory for using the programme under Egyptian conditions, according to the findings.

Arbat et al., [30] used Simulation HYDRUS-2D software to conduct a field experiment for rice production, which was effective in predicting soil water distribution, deep drainage, and plant water extraction. Furthermore, HYDRUS-2D simulations may be useful in determining the best position for soil water probes to effectively manage the Sub surface drip irrigation in rice.

seasons to assess the SALTMED model's efficiency in terms of soil moisture, total dry matter, and yield simulation. Soil moisture, total dry matter, yield, and water productivity were all correctly predicted by the model. As a result, the model could be used to control crops, water, and land under current and future climate change.

Marwa et al., [32] used the SALTMED model to forecast the effect of two future climate data scenarios on peas parameters in the year 2040. The results showed that the model is a good method for forecasting crop parameters, assessing the potential impact of various scenarios on irrigation management, and that the model predicts an increase in projected water requirements in both scenarios.

ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) refers to a computer's or a computer-controlled robot's ability to perform tasks. The term is often applied to a project aimed at developing systems with human-like cognitive abilities, such as the ability to think, discover meaning, generalise, and learn from previous experiences.

In 1955, Stanford Professor John McCarthy coined the word "artificial intelligence," which he described as "the science and engineering of making intelligent machines." Many studies have shown that humans can programme machines to act in clever ways, such as playing chess, but today we focus on machines that can learn, at least in part, like humans [33]

It has been demonstrated that computers can be programmed to perform extremely complex tasks with ease, such as discovering proofs for mathematical theorems or playing chess, since the advent of the digital computer in the 1940s. In general, DL systems are based on the layer-wise architecture of the human brain. Despite continuing improvements in computer processing speed and memory capacity, no programme has yet to match the flexibility of humans [34].

However, some algorithms have surpassed the performance standards of human experts and specialists in performing specific tasks, and artificial intelligence in this restricted context can be used in applications as diverse.

Farmers' satisfaction about their agricultural yields depends on accurate predictions of irrigation needs and crop yields. The foresight contributes significantly to lowering production costs and increasing crop yields. It's also difficult to forecast crop yields precisely.

The precise estimation of irrigation and crop yields are also beneficial to the government, as it aids in the preparation of various schemes for planning irrigation water requirements.

In this section we will discuss various Artificial Intelligence techniques and applications for yield prediction and smart irrigation.

This section recognises previous breakthroughs as well as Artificial Intelligence-based techniques in precision irrigation, especially for yield prediction and smart irrigation. A system based on Artificial Intelligence provides adequate knowledge about yields and its related to smart irrigation system management.

Taking into account that deep learning is a subset of machine learning that enables computers to solve more complex problems and Machine learning, meanwhile, is a subset of AI. Figure (2) shows the relationship between AI, machine learning and deep learning.

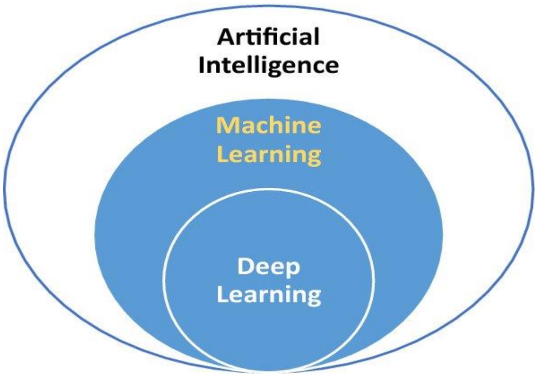

Figure (2): Relationship between AI, Machine learning and deep learning [34]

MACHINE LEARNING AND SMART IRRIGATION

For enhancing irrigation and water management in agriculture, many researchers and organisations have proposed the idea of Machine Learning and Smart IOT-based systems (Internet of Things-based systems). Traditional irrigation methods were inefficient, so in order to automate the irrigation system and track the field, some additional technology, such as artificial intelligence, are needed so that the system can predict agriculture data, future results and function accordingly. Machine learning is a form of artificial intelligence. The Machine to Machine Communication is assisted by machine learning, which is a subset of artificial intelligence (M2M). The whole system learns how to act and functions like a human brain [35].

Machine learning (ML) has risen to prominence alongside big data and high-performance computing to open up new avenues for unravelling, quantifying, and understanding data-intensive processes in agricultural operations.

A performance metric that improves with experience is used to assess the ML model's performance in a given task. Various statistical and mathematical methods are used to measure the efficiency of ML models and algorithms.

Using the experience gained during the training phase, the trained model can be used to identify, predict, or cluster new examples (testing data) after the learning process is completed. Figure (3) depicts a standard machine learning approach [14].

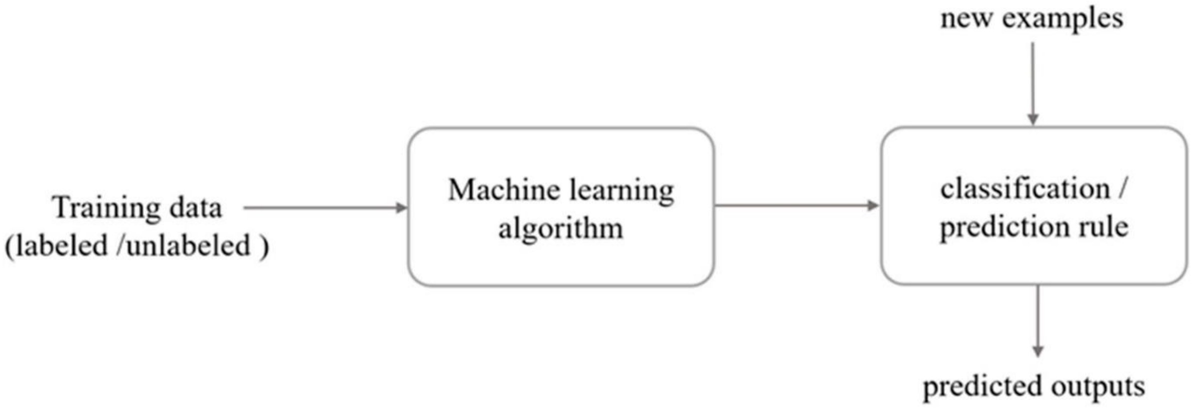

Figure (3): A typical machine learning approach [14]

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Hou et al., [36] carried out an experiment to predict soil moisture by using an artificial neural network with climate data, the results were in good agreement with real data. Cai et al., [37] found that deep learning regression network (DNNR) can predict the moisture patterns of regions (Shunyi and Daxing) with high degree of generalisation and scalability and has the ability to keep prediction error near zero. This model can be used to forecast soil moisture and provide technical support for irrigation strategies and drought management.

The DNNR model has the advantage of being able to compare or discover feature combinations that have never been seen before, as well as being good at fusing secret feature attributes, minimising feature engineering complexity and enhancing the model's generalisation capability. Figure 3 depicts the DNNR network structure.

Al-Naji et al., [38] presented a new non-contact vision system based on an RGB camera that uses deep learning and a feed-forward back propagation neural network to predict the irrigation requirements of loam soil. JPEG or TIFF file formats are used by most digital cameras to capture images in the red (R), green (G), and blue (B) colour spaces. By analysing variations in soil colour recorded by an RGB camera at various distances, periods, and illumination levels, it is possible to control water use under various conditions Figure (4).

The accurate estimation of evapotranspiration is a dynamic process that is critical for crop production resource management as well as irrigation system design and operation management. ML application used for predicting and identifying agricultural soil properties, such as soil drying, condition, temperature, and moisture content estimation. Soil is a dynamic natural resource with a variety of processes and mechanisms, for that it is difficult to be comprehend. Researchers may use soil properties to figure out how ecosystems function and how agriculture affects them. Improved soil management can be achieved by accurately estimating soil conditions.

SMART IRRIGATION

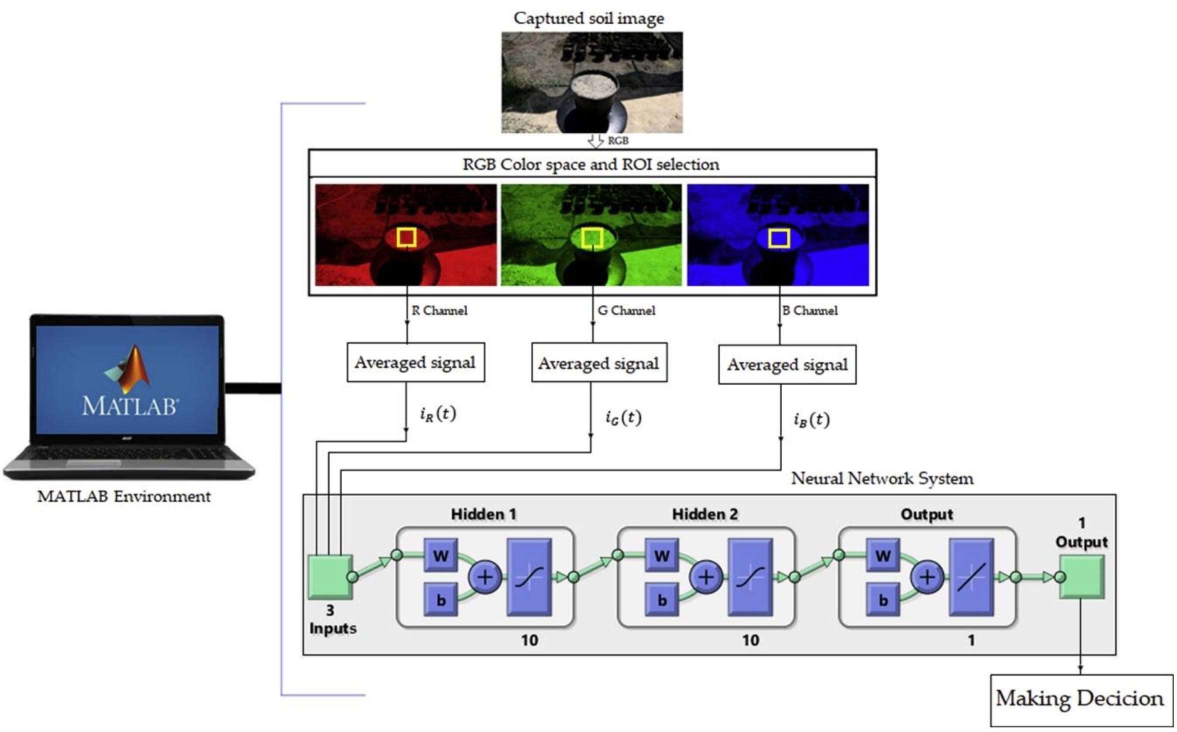
Smart irrigation techniques have the ability to increase water application efficiency, reducing the environmental effect of agriculture while also providing farmers with a financial benefit.

For enhancing irrigation and water management in agriculture, many researchers and organisations have proposed the idea of Machine Learning and Smart internet of things IOT-based systems [35].

Smart agriculture entails using a variety of Information and Communication Technologies (ICTs) to boost productivity in a way that is both sustainable and profitable. The paradigm is technology agnostic; it envisions the provision of a set of technologies that can be used as required depending on the situation [39].

Low-cost smart irrigation systems were designed by researchers. Jha et al., [40] conducted a comprehensive study of such irrigation systems, pointing out that smart irrigation systems can save a significant amount of water, which can be used for other essential human purposes.

In smart irrigation, the microcontrollers take over after the sensors have collected the data. It's a crucial part of the whole automatic irrigation system. With the assistance of a transformer, a bridge rectifier circuit (a component of electronic power supplies that rectifies Alternating Current AC input to Direct Current DC output), and a voltage regulator, the entire circuit is powered up to 5 Volts.



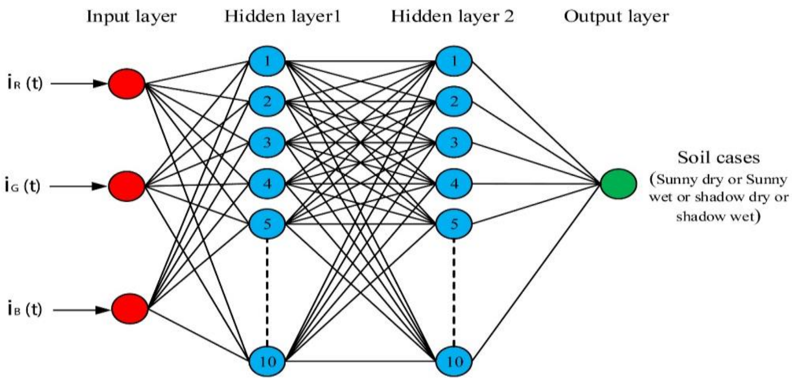


Figure (4): The block diagram using deep learning structure [38]

Developing systems that automates irrigation with AI and IoT technologies intelligently by gathering related data about different crops, growth rate, and irrigation demands become essential. These technologies are capable of controlling frequent climate change, weather and irrigation forecasting, etc. [41].

Smart embedded systems are used to automate these intelligent irrigation systems. As shown in Figure (5), smart embedded systems can be created using a variety of technologies/devices, including the Raspberry Pi, Arduino, power unit, different sensors for temperature, moisture , M L, and IoT [42].

After that, the microcontroller is set up. The signals from the sensors are received by the microcontroller. For transmitting the sensed soil conditions, the OP-AMP serves as an interface between the sensors and the microcontroller. As a result, the irrigator pumps work based on knowledge about the soil properties at the time of operation Figure (6). Moisture sensors can also be used to automate the irrigation process.

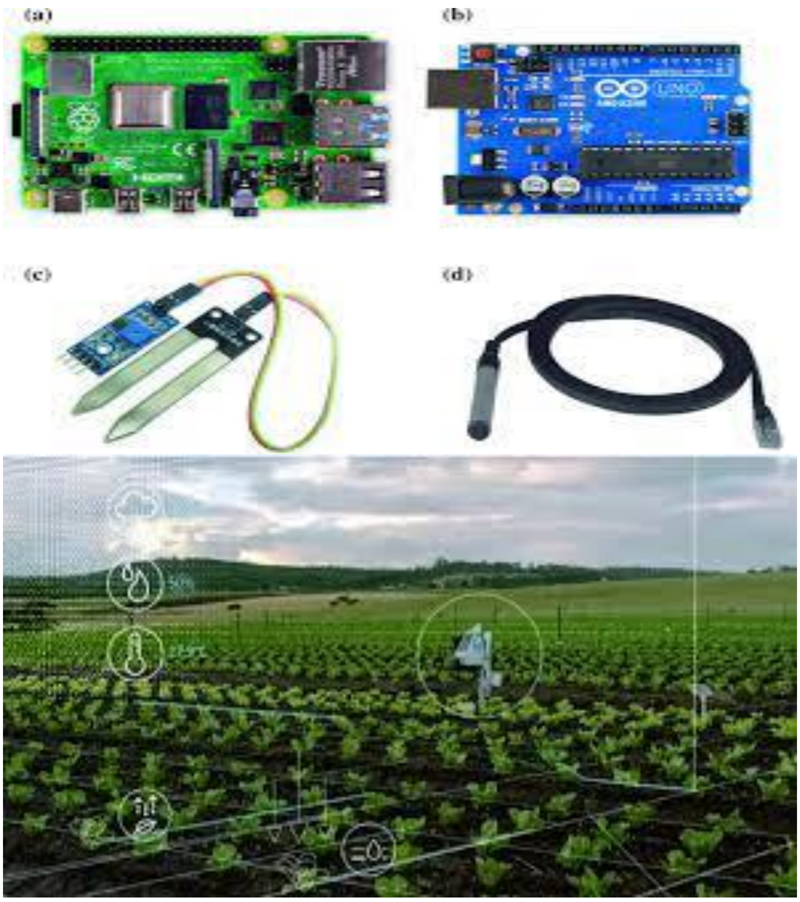


Figure (5): Various devices for smart implementing smart irrigation systems: (a) Raspberry Pi, (b) Arduino, (c) soil moisture sensor, (d) temperature sensor

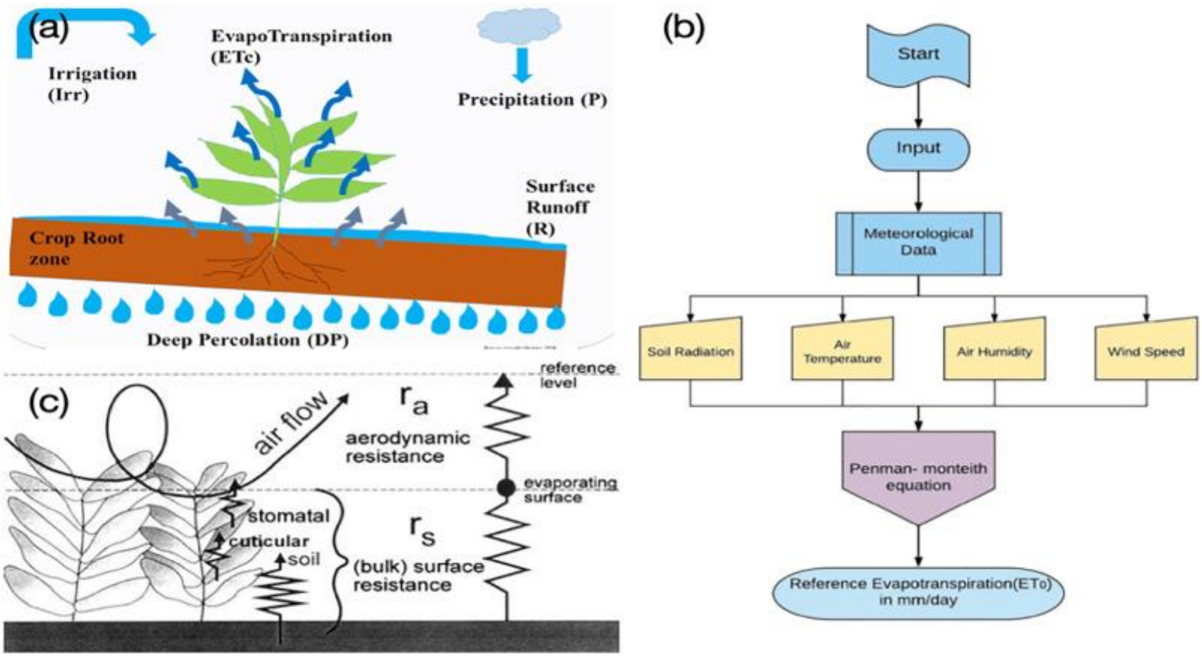


Figure (6): (a) Soil Water Balance Components for Evapotranspiration Model Source: University of Minnesota (b) Flowchart for Reference Evapotranspiration (c) FAO Penman-Monteith method [40]

Priya and Madhumitha [43] used a moisture sensor device to determine the amount of water in the soil. The pump will turn on when the amount of water in the soil decreases, and it will turn off until the soil has received enough water, GSM module was used to send messages to the owner when the soil's water content was low and high, as well as when the irrigation system was turned on and off.

Knowledge-driven "smart" irrigation, according to Shi et al., [44] aims to achieve specifically targeted crop yield and/or irrigation water use efficiency (WUE). They used numerical simulation to develop a coupled crop growth and soil water transport model that they used to schedule irrigation for drip-irrigated and film-mulched maize.

ROBOT AND AUTOMATION

The applications of automation and smart systems in the field of irrigation that will help to make the irrigation process efficient and reduce the wastage of water [45].

Nagaraja et al., [46] presented a completely autonomous system for watering indoor potted plants on a level floor. A mobile robot and a temperature-humidity sensing module make up the device. The device is completely adaptable to any setting and uses a temperature-humidity sensing module to account for the plants' watering requirements.

Wireless connectivity is used to communicate between the mobile robot and the sensing module in the fully automated watering system. A Radio Frequency Identification (RFID) module, a microcontroller, an on-board water tank, and an associated water pump are all included in this gardening robot.

It is capable of sensing the plants' watering requirements, finding them, and then watering them without the need for human interference. The robot is moved to the potted plant by following a predetermined direction. Each potted plant has an RFID tag attached to it for identification. Architecture of the Autonomous System and Plant Watering Autonomous Mobile Robot are shown in Figures (7).

Shobila and Mood [47] developed an effective system for periodically monitoring the condition of the crop by using a robot that moves around in the field and displays the crop's condition on PC. The developed automated irrigation system demonstrates that water consumption can be reduced for a given amount of fresh biomass output. Aside from the financial benefits of conserving water, the value of preserving this natural resource justifies the use of these irrigation systems.

For the sprinkler irrigation classic system, Sature et al., [48] proposed and created an automatic guide vehicle (AGV) with the capability of changing sprinklers on time and in appropriate positions. The built AGV was tested in a computer setting, and the results were satisfactory. Robots are used as a complement to irrigation systems in order to reduce manpower shortages and save money.

Adeodu et al., [49] developed an autonomous mobile plant irrigation robot. The system uses an Xbee Series 1wireless communication to communicate between the mobile robot and a moisture sensing module which

is fully adaptive to a semi-structured environment taking into account the watering needs of the plants.
The plant irrigation mobile robot was created to water a specific area of land without human intervention. The robot's actions are divided into two main phases: moisture sensing and watering, which are carried out by two modules.
The YL-69 soil sensor is used to detect moisture and is operated by an ATmega328 microcontroller based on the Arduino framework. DC motors and a water pump relay built into another Arduino microcontroller power the robot's irrigation and mobility. Watering operation is based on soil moisture data.
Field robots are already being used to help farmers measure, map and optimise water and irrigation use. Robots could help with irrigation by directing water to the right place at the right time. Intelligent irrigation systems may adjust their irrigation strategy in response to changing weather conditions and crop growth status, reducing the amount of fresh water used while maintaining yields. Computer-controlled irrigation equipment then implements the optimised plan (e.g., when, where, and how much water to use) [50].

DRONES IN IRRIGATION

The use of drones would speed up and improve the quality of production, resulting in increased output. Simultaneously, the cost of IoT implementation must be reduced. Small farmers will be able to use smart agriculture as a result of this. Drones are becoming a useful tool in agriculture for conserving water.
As the demand for more efficient water use increases, having a drone that can track and control irrigation becomes increasingly important. Drones can see problems that are invisible to the naked eye using thermal and traditional cameras.
Drones with their thermal imaging capability could be useful and productive in identifying soil moisture variance and its effect on field crop water status Figure (8). Drone imagery is often used to track irrigation once the crop is grown. Drones are less expensive to use when testing crop genotypes for drought tolerance. Drones are fast, and data can be collected multiple times. Drones could be used by plant breeders to screen crop genotypes for drought stress in the future [51].

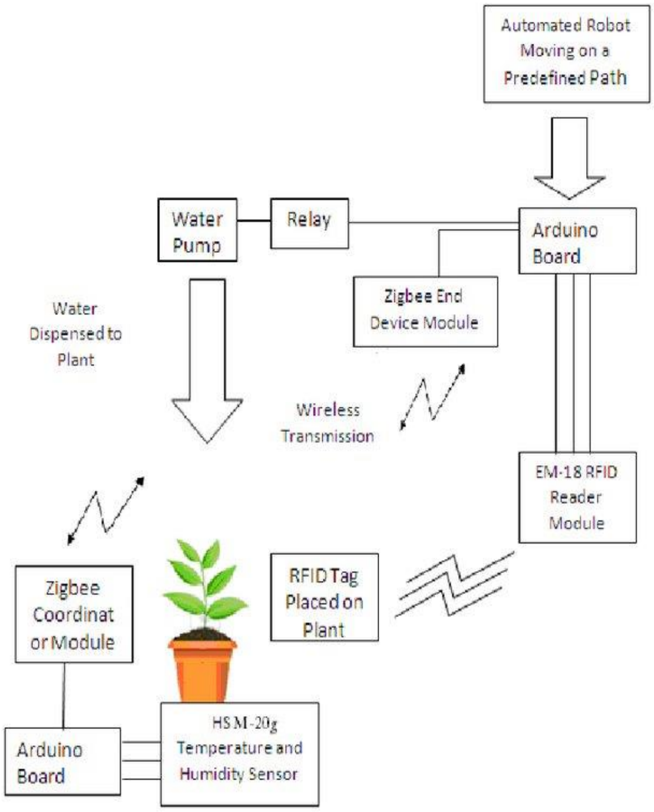


Figure (7): Architecture of the Autonomous System [46]

Figure (8): Drones with their thermal imaging capability [51]

Unmanned aeronautical vehicles (UAVs) or unmanned etherealframeworks (UAS), otherwise called automatons, in a mechanical settingare unmanned aircrafts that can be remotely controlled [52].

Managing multiple irrigation pivots is a difficult job, particularly for large growers with multiple fields spread across a county. Mid-season observation of the nozzles and sprinklers for watering device supplies becomes a crucial activity when crops such as sorghum or jowar, corn, start arriving at certain heights. If drone technology can be made affordable, it could provide some useful information about when and where to apply specific amounts of water to the crop. Farmers with the right irrigation technology could use this data to accurately apply irrigation water at different rates in the field, rather than at the same rate everywhere, which would waste water [53].

Drones can be extremely useful at the beginning of the crop cycle. They create detailed 3-D maps for early soil analysis and seed planting pattern preparation. Drone-assisted soil analysis provides data for irrigation and nitrogen control after planting. Drones equipped with hyper-spectral, multispectral, or thermal sensors can detect areas of a field that are dry or in need of improvement. Drones can also calculate the vegetation index, which defines the relative density and health of the crop, and display the heat signature, which is the amount of energy or heat the crop emits, while the crop is growing [54].

Smart drones have sensors built into their Unmanned Aerial Vehicles (UAVs) that feed into a network infrastructure that allows them to communicate with other devices through Internet technologies, making them smart.

It's time-consuming to manage multiple irrigation pivots, particularly for large growers. Mid-season inspections of the nozzles and sprinklers on irrigation machinery that provide the much-needed water become a painstaking exercise once crops like corn hit certain heights. Drones would be extremely beneficial in controlling irrigation equipment [55].

CONCLUSION AND RECOMMENDATIONS

Agriculture is facing major challenges such as inefficient irrigation systems, climate changes, groundwater intensity, food shortages as well as reuse of food and water wastes, and much more. The acceptance of different cognitive solutions has a significant impact on the fate of cultivating. With the growing population, there is a pressing need to provide more food and agricultural crops, which necessitates the supply of sufficient water. In agriculture and other human activities, water is still the most important factor.

Traditional irrigation water management methods are insufficient to face the rising demand. Artificial intelligence and simulation models are two new technologies that can help with irrigation and water conservation. Farmers will benefit from the technology because it will help them achieve higher yields and a more consistent seasonal crop.The Artificial intelligence is useful to be used in irrigation practice and to predict weather and other agricultural conditions. Most of the farmers' concerns would be alleviated by accurate projection or prediction using AI technology. AI-powered sensors are extremely useful for extracting essential agricultural data. The information will be helpful in improving efficiency of irrigation application.

Those designing the next generation of agricultural systems models, data, and information systems should embrace new technologies and knowledge. Smart phones and networking, remote sensing, open source software tools, and cloud computing as a way of allowing wide access to powerful tools are all examples of modern technology. Despite the fact that large-scale research is still underway and some implementations are already on the market, the industry of AI and simulation models remains underserved. Farming is also in its infancy when it comes to dealing with real-world problems and solving them with automated decision-making and predictive solutions.

Applications must be more reliable in order to explore the vast potential of AI in agriculture. Only then will it be capable of handling regular changes in external circumstances, facilitating real-time decision making, and using an effective framework/platform for efficiently gathering contextual data.Another significant factor is the exorbitant expense of various cognitive farming solutions available on the market.

Despite the development of these technologies, the industry of simulation models and artificial intelligence is still in its infancy, and research in this field is still ongoing to become more reliable, easy to use, and less expensive to ensure that it reaches farmers in an affordable way, which requires attention to this area and its inclusion in research plan of universities and research centres in Egypt to keep pace with progress in this field.

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