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SURVEY ARTICLE

A Survey Towards Decision Support System on Smart Irrigation Scheduling Using Machine Learning approaches

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Abstract

From last decade, Big data analytics and machine learning is a hotspot research area in the domain of agriculture. Agriculture analytics is a data intensive multidisciplinary problem. Big data analytics becomes a key technology to perform analysis of voluminous data. Irrigation water management is a challenging task for sustainable agriculture. It depends on various parameters related to climate, soil and weather conditions. For accurate estimation of requirement of water for a crop a strong modeling is required. This paper aims to review the application of big data based decision support system framework for sustainable water irrigation management using intelligent learning approaches. We examined how such developments can be leveraged to design and implement the next generation of data, models, analytics and decision support tools for agriculture irrigation water system. Moreover, water irrigation management need to rapidly adapt state-of-the-art using big data technologies and ICT information technologies with the focus of developing application based on analytical modeling approach. This study introduces the area of research, including a irrigation water management in smart agriculture, the crop water model requirement, and the methods of irrigation scheduling, decision support system, and research motivation.

1 Introduction

WATER-Every drop is precious, save it. Water is the main limiting factor of agricultural development in semi-arid and arid climates. It is a critical input for enhancing agricultural productivity. Arthur Keith said that the advancement of agriculture is the first major step for civilized life [1]. Even after six decades of planned development, agriculture has played an important role in the Indian economy. However, the agriculture sector of India has been transformed via the effective deployment of Information and Communication Technologies (ICTs) in traditional to modern practices which provide various services (such as- IoT agriculture, smart water management, soil management, plant diseases, crop management, geo-spatial image and livestock monitoring).

In India, the demand of water for the agriculture and industry sectors is continuously increasing to fulfill the needs of 1.366 billion people. Central Indian Punjab is well-known for its agricultural activities and has occupied a high percentage of the land area all over India, and its agricultural production mainly depends on irrigation.

Punjab has 97.95% highest gross irrigation of the total cropped area [2]. Recently, the achievement of the Green Revolution is endangered by a significant decline in water resources. As a result, water conservation and precision agriculture are becoming vital issues in tropical climate areas. Wheat and Maize are the most commonly cultivated crops and have high water consumption in Punjab, India. The major challenge in agriculture sustainability and dawdling is due to climate change; therefore, every drop of freshwater needs to be utilize effectively and efficiently.

To overcome these challenges, the multivariate, complex, and unpredictable agricultural ecosystems must be well understood by continuously analyzing, measuring, and monitoring several physical aspects and phenomena [3]. New technologies and knowledge can help in this complex decision-making. The fundamental idea is that the DSS should serve as a farm management tool, supporting farm managers in making decisions on irrigation, whether to irrigate and, if so, which field with how much water. Wani et al. [4] presented a thorough investigation to evaluate the possibility of using Machine Learning models to identify plant diseases.

In the early twentieth century, irrigation is the most crucial practice no doubt and needs effective utilization.

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Farmers required to predict the need of water for the crops, to confirm the data provided by agricultural weather stations or to get insight the free water surface evaporation in lakes or dams. Agricultural irrigation scheduling is becoming a very important managerial activity whose ultimate purpose is to achieve effective and efficient utilization of water. The primary objective of good irrigation scheduling is to apply the right amount of water at right time.

Irrigation scheduling improves the water use efficiency and focus on evapotranspiration (ET) estimation methods for understanding of spatial variations of ET. It determine irrigation applications such as identifying the water balance component, integrated various sensing technologies into irrigation scheduling models and control, new improved sensor technology and integrated water quality constraints into irrigation scheduling and control [5]. Figure 1 presents the six identified relevant works, indicating the smart water management related research work such as crop water modeling, soil monitoring, water quality, drones field monitoring, weather forecasting, and irrigation scheduling.

The ultimate irrigation potential of India has been estimated to be 139.5 million ha, comprising 58.5 million ha from major and medium schemes, 15 million ha from minor irrigation schemes, 66 million ha from groundwater exploitation, and an estimated 77 million ha beyond 2025 from freshwater use for irrigation [6]. It is approximated that after gaining the full potential of the irrigation, nearly 50% of the total cultivated area will hold out rain-fed.

Fig. 1 Smart water management in smart agriculture

Irrigation is the most important factor for escalating the agricultural production of plants. It is essential to determine the quantity of water to get the optimal benefits from the irrigation, which depends on some factors such as the environment, type of crop, subsurface geo-hydrological condition, and the stage of its growth.

The questions arise in the irrigation scheduling are as follows: (i) How to apply irrigation water?, (ii) How much to irrigate?, (iii) When to irrigate. Currently, irrigation decision-making systems are enforced to the agricultural field aiming for specific crop at a given area [7]. It is difficult to be practiced to different crops and areas. Under the growing environment, the amount of irrigation is defined as the depth of water required to meet the crop water loss through evapotranspiration. It can be obtained via prediction using indirect channels or field measurement techniques. However, the amount and timing of water have major impact on quality of crop and its yield. Several methods are applied for the irrigation scheduling such as pan evaporation, soil moisture basis, leaf water potential, and based on growth-stages. The demand of water can be fulfill by full or partial irrigation in all methods.

1.1 Motivation

As technology rapidly spread in a few decades, precision agriculture is the key to fostering a new revolution in Irrigation scheduling. The United Nations statistical data indicate that agriculture consumes 70% of the overall use of water worldwide, compared with 20% for industry and 10% for domestic use [8]. To ensure the proper use of water supplies in irrigation we need more effective technologies. Automatic irrigation scheduling techniques replaced manual irrigation which was based upon crop water estimation. The crop evapotranspiration can be determined by weather parameters such as max–min temperature, humidity, wind speed, solar radiations, and even the crop factors such as the stage of growth, crop height, and the soil properties for the development of irrigation scheduling. The machine learning and deep learning advanced technologies provide direction and motivation to propose a novel application on crop water modeling. The influence of several factors on crop yields and temperature, precipitation have been found to have maximum influence on the yields of different crops [9].

2 Reference Evapotranspiration ET_o

"Evapotranspiration contains two processes, evaporation in which water is lost from the soil and plant surface, and transpiration from plant surfaces to the atmosphere" [10].

The water irrigation is enforced to match the needs of evapotranspiration of crop. Therefore, the irrigation scheduling needs to estimate the daily crop evapotranspiration accurately. Evapotranspiration of crops differs significantly over the growing season mainly due to alterations in climatic conditions and crop cover. It also varies among the crops. The information about crop water demand (i.e., ET) is a crucial practical consideration in the planning, developing, and working of water and irrigation management systems. Figure 2 presented the concept of ET_o.

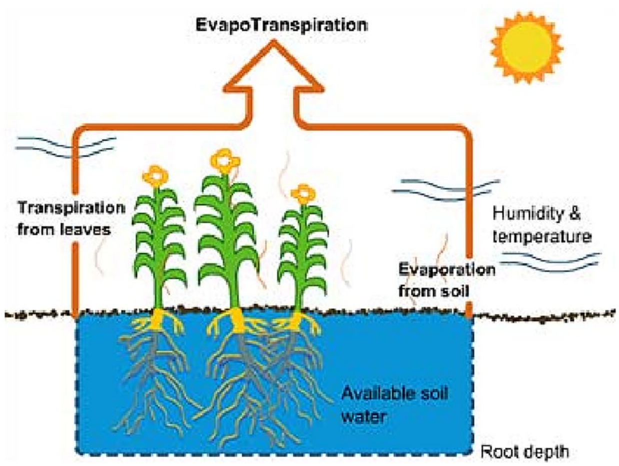

Fig. 2 Reference evapotranspiration (ET_o) process

Table 1 presented the ET that affecting by weather element. The reference evapotranspiration is approximated from meteorological data (humidity, temperature, wind run/wind speed, sunshine hours/solar radiation) by using the Penman-Monteith equation. However, the adjusted pan evaporation measurements are also used.

2.1 Factors Affecting ET_o

Climate and weather play crucial role in determining long-term and day-to-day activities in the agriculture. The demand of crop water is determined largely by weather variables. Rainfall is the foremost weather variable that affects the water resources development planning, irrigation planning and agricultural cropping. The main climatic/weather components crucial for agriculture are rainfall, maximum/minimum temperature, solar radiation, sunshine duration, humidity, photo-period or sunshine hour, wind speed, and night temperature [11] as depicted in Fig. 3. Table 2 shows the different empirical methods with weather parameters for estimation of ET_o.

Weather elements controls the crop water demand and crop ET. The ET depends upon the different weather elements such as humidity, temperature, sunshine hour, solar

Table 1 Weather affecting parameters

Name	Models	References
Solar Radiation	Richardson Model $R_g/R_a = a(T_{max} - T_{min})^b$	Richardson [12]
	Angstrom Model $R_g = R_a(a+b)(n/N)$	Angstrom [13]
	Regression Model $R_g = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n$	Ali et al. [14]
Air Temperature	$T_{mean} = \dfrac{T_max + T_{min}}{2}$	Allen et al. [15]
Air Humidity	The most commonly used expressions:	ALi [16]
	Absolute humidity, relative humidity, specific humidity, perceptible water	
	Instruments used for measuring humidity is called:	
	Psychrometer, hair hygrometer, dew-point hygrometer	
Wind	$\frac{\bar{v}}{v} = \frac{z}{z_1}^k$, $\frac{\bar{v}}{v_1} = \dfrac{ln(z/z_0+1)}{ln(z1/z_0+1)}$	Linsley [17]
		Sutton [18]
Sunshine hour	$N = (2/15)cos^{-1}(-tan\delta tan\phi)$	Duffie and Beckman [19]
Rainfall	Arithmetic average, Theissen weight, Isohyetal weight	Ali (2010) [16]
	$P = (P_1 + P_2 + \cdots + P_n)/n$ $P = (P_A.W_A) + (P_B.W_B) + (P_C.W_C) + ..$	
	$P = \dfrac{\sum P_iA_i}{\sum A_i}$	
	Effective rainfall=Total rainfall-Surface runoff	

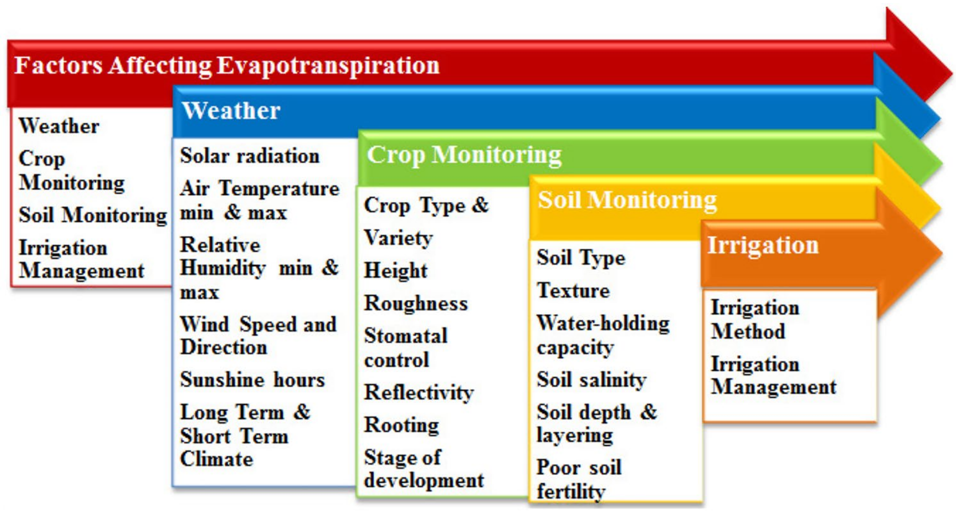

Fig. 3 Factors affecting evapotranspiration

Table 2 ET_o estimation empirical methods

Name	Formula	Parameters	References
A standard scientific empirical model			
FAO Penman Monteith	$ET_o = \frac{0.0864}{\lambda}.\frac{\triangle(R_N - G) + c_p\rho_a DPV/r_a}{\triangle + \gamma(1 + r_c/r_a)}$	T_{mean}, T_{max}, T_{min}, ws, N, RH	Allen et al. [15]
Temperature based estimation models			
FAO Blaney-Criddle method	$ET_o = [\rho(0.46T + 8)]$	T_{mean}, p	Blaney and Criddle [26]
Rational use of the FAO Blaney-Criddle method	$ET_o = [k\rho(0.46T + 8.13)(1 + 0.0001E)]$	T_{mean}, P, N, RH_{min}, ws, E	Allen and Pruitt [27]
Hargreaves and Samani method	$ET_o = (0.00023R_a)(T_{mean} + 17.8)TD^{0.5}$	T_{mean}, T_{max}, T_{min}, R_a	Hargreaves and Samani method [28]
Hargreaves and Samani method 1	$ET_o = (0.0030 * 0.408R_a)(T_{mean} + 20)TD^{0.4}$	T_{mean}, T_{max}, T_{min}, R_a	Droggers and Allen [29]
Thornthwaite (TH)	$ET_(o) = 16\frac{T_{mean}}{i}^{i}$	T_{mean}, i	Thornthwaite [30]
Pan evaporation method	$ET_o = K_p E_{pan}$	T_{mean}, RH, N, rainfall	Kohler [31]
Radiation based estimation models			
FAO radiation method	$ET_o = a + b[\frac{\triangle}{\triangle + gamma} * R_s]$	R_s, T_{mean}	Doorenbos and Pruitt [32]
Priestley-Taylor (PT)	- $ET_o = 1.26\frac{\triangle}{\triangle + \gamma} * \frac{R_n - G}{\lambda}]$	T_{mean}, T_{max}, T_{min}, RH, N, ψ	Priestley and Taylor [33]
Jesen-Haise (JH)	$ET_o = 0.408 * C_{T_{mean}} * (T - T_k) * K_{T_{mean}} * R_a * TD^{0.5}$	T_{mean}, TD, R_a	Jensen et al. [34]

radiation, wind speed, etc. It is also affected by rainfall. The weather elements affect ET as follows:

2.2 FAO ET_o Estimation Method

There are various mathematical models used to calculate the reference evapotranspiration (ET_o). The updated procedures for calculating the ET_o were introduced by FAO. The Food and Agriculture Organization (FAO) recommends the method for calculating the ET_o are as follows:

Although, the method FAO-56 Penman–Monteith (Allen et al. 1998) [10] is the most dominant as compared to others empirical methods [20, 21]. But, it requires several climatic data factors [22].

The FAO-56 Penman-Monteith (FAO-PM56) [10] has been broadly used to analyze ET_o from meteorological factors and it is suggested as the standard technique by the Food and Agriculture Organization of the United Nations (FAO) [23] and calculated by Eq. (1).

$$ET_o = \frac{0.408 \cdot \Delta \cdot (R_n - G) + \gamma \cdot \frac{900}{T_{mean}+273} \cdot u_2 \cdot (e_s - e_a)}{\Delta + \gamma(1 + 0.34W_s)} \tag{1}$$

where, ET_o is the reference evapotranspiration (mm/day^{-1}); Δ= slope of saturation vapor pressure function (kPa °C^{-1}); R_n= net radiation (MJ $m^{-2}day^{-1}$); γ = psychometric constant (kPa °C^{-1}); G = soil heat flux density (MJ $m^{-2}day^{-1}$); W_s = average 24-h wind speed at 2 m height (ms^{-1}); T_{mean} = mean air temperature (°C); e_a = actual vapour pressure(kPa); e_s = saturation vapour pressure(kPa); and ($e_s - e_a$) = vapour pressure deficit (kPa).

However, ET_o can be determined accurately by this method, large scale meteorological data requirement at specific spatio-temporal scales (vapor pressure deficit, wind speed, minimum and maximum air temperatures, and solar radiation) are quite often not available in many developing countries [24]. Thus, the alternate models are needed to estimate ET_o when the available data are either insufficient or limited. So, it is important to explore a simpler model to calculate ET_o using fewer weather properties and a reasonable precision.

The need of crop water depends on some factors: crop growth/stages, crop type and the climate are given in detail [25]:

3 Crop Evapotranspiration ET_c

> "The crop evapotranspiration denoted as ET_c,is the crop water requirements or crop water need."

The need for crop water is the depth (or quantify of water required to cope with the loss of water through evapotranspiration. In other words, water needs to be cultivated optimally by different crops. Crop-growth models were developed to improve the understanding of crop dynamics and to predict crop growth and production under various agronomic conditions [35]. The continuous monitoring of the soil status water, the conditions of crop growth, and its spatial and temporal patterns will help in irrigation and precision water planning. Evaporation and transpiration variations in the field and grass crops can be integrated into dual crop coefficient or single crop coefficient (K_c): a soil evaporation coefficient (K_e) and a basal crop (K_cb) and calculated by Eq. (2).

$$(K_c) = (K_cb) + (K_e). \tag{2}$$

3.1 Climate Based ET_c

The combination of two different processes by which water evaporates from the soil surface and transpiration from the plant is referred as evapotranspiration. It is determined by climatic factors including solar radiation, temperature, wind, and humidity as well as environmental factors. The evaporation account for approximately 10% of the overall evapotranspiration and the transpiration of crops constitutes the remaining 90%. Hence, there is a need for crop water in hot, dry, windy, and sunny areas. For the lowest values when the wind is cold, humid, and cloudy, with little to no wind. Climate impact on crop water requirements is determined by reference crop evapotranspiration ET_o and generally expressed per unit of time in millimeters., e.g. mm/day, mm/month, or mm/season.

3.1.1 Crop Type

The effect of the crop type in daily crop water requirements is often referred to as a fully grown crop; Plant height has reached maximum; Plants cover the ground optimally; probably they began to flowering or developing to set grain; The water demand is greatest when the crop is fully cultivated. Their water needs are called the "peak period".

The type of crop that has also affected the total growing duration of crop development is known by seasonal crop water need and can be obtained. The best possible local data can be obtained on the duration of the total seasons of the various plants cultivated in a region. Such data can be collected from, for example, the seed supplier, the Extension Service, the Irrigation Department, or the Ministry of Agriculture.

3.1.2 Growth Stages of the Crop

While planting and in the initial stage, evaporation is more essential than transpiration. When the crop is fully developed, the need for crop water is estimated to be 50% during the mid-season phase. At the stage of development, the crop demand moderately increases from 50% of the maximum crop water requirement to the maximum crop water. Thus, the maximum amount of crop water is extended to the end of crop development stage, which is the starting of mid-season stage.

The value of K_c depends on different factors such as canopy cover density, agriculture operations, weather variable, type of crop, soil moisture, and growth stage [10]. The idea of crop coefficient K_c is proposed by Jensen [36] and has been improved by many researchers [37, 38].

However, K_c method has the capability to determine the actual crop evapotranspiration ET_c precisely. According to the FAO methodology, the four growing stages of a crop are the initial stage, crop development stage, mid-season stage, and end-season stage (Allen et al. 1998) [10]. The crop coefficient method can be expressed as follows:

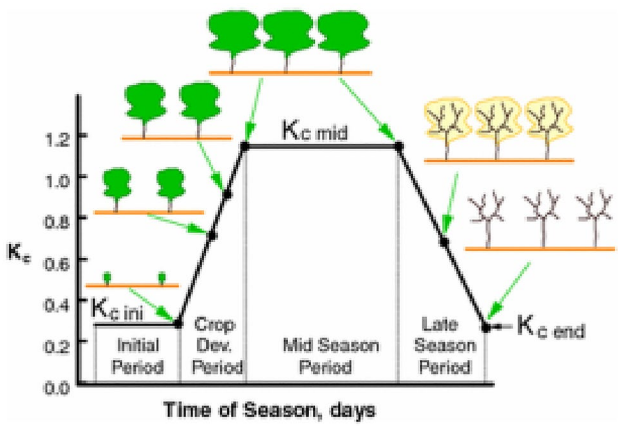

Fig. 4 Various crop-growth developement stages

The two-step crop coefficient K_c reference evapotranspiration has been a successful method to predict the evapotranspiration (ET) and crop water requirements. The total growing period is divided into 4 growth stages shown in Fig. 4 [39]:

- *The initial stage* the period ranges from transplanting or sowing till crop covers the 10% of ground.
- *The crop development stage* the period begins at the completion of the initial stage and remains until the full ground has been covered (ground cover 70–80%). It does not certainly mean that the crop is at its maximum height.
- *The mid-season stage* the period begins at the completion of the crop development stage and remains till maturity; it consists grain-setting and flowering.
- *The late-season stage* the period starts at the completion of mid-season stage and remains until the last day of the harvest; it consists ripening.

$$ET_c = K_c \times ET_o \tag{3}$$

where ET_c represents the requirement of crop water (mm d^{-1}), ET_o the reference crop water requirement (mm d^{-1}), and K_c the crop coefficient and calculated by Eq. (3). Besides, Kingra et al. (2004) computed crop water requirement for Wheat and transplanted Rice at Ludhiana, reported that the Wheat crop used about 315 mm water whereas the rice crop used about 780 mm water during its growing season [40]. Saggi et al. [41] collected the K_c values as case study from Punjab agricultural University (PAU), Ludhiana and estimated the ET_c for two crops. The K_c values of $Wheat_1$ crop were 0.4, 1.15 & 0.4 while for $Wheat_2$ were 0.5, 1.36, 1.42, and 0.42 for the initial, mid and last stage of growth respectively. The length of time (days) for four seasons of $Wheat_1$ were 29, 55, 14 32 days while for $Wheat_2$ 24, 46, 35, 42 days. The K_c values of Maize crop were 0.7, 0.85, 1.15 & 1.05 for the initial, mid, and end-stage of growth respectively. The length of time (days) for four seasons of Maize were 35, 18, 17, and 15 days used in different stages. Detail of selected crops and period of data for the study.

4 Irrigation Scheduling

In 1996, Howell explored the effects on water use and irrigation scheduling [42]. It is an application mechanism that can lead to the effective and efficient use of water. This efficiency can be enhanced by using advanced methods of irrigation. However, even in advanced irrigation methods, irrigation scheduling at the farm level is required. It is necessary when rainfall is deficient to remunerate for the water lost by evapotranspiration. The irrigation water need is described as the crop water requirement minus the fruitful rainfall. It is defined in mm/month or mm/day. The main goal of good irrigation scheduling is to apply the correct amount of water at the right time, and make sure that water is accessible when the crop requires it.

According to predetermined schedules, the irrigation water is supplied to the cultivation by keep track of the following [43]:

- The status of soil water;
- The need of crop water.

The purpose of our research work is to present, analyze, and optimize some measure of performance of the crop production under a set of specified conditions, such as the limited or unlimited total volume of water for the growing season. The main factors that influence the solution and implementation of the irrigation scheduling problem are the characteristics of climate soil, crop, irrigation water, and irrigation technology.

Judicious usage of water for crop production needs knowledge of water quality, soil, weather, crop, and drainage situation. The increase in efficiency of pumping systems and conveyance need to review.

The soil types and climatic conditions have a considerable effect on the major practical aspects of irrigation such as how much amount of water should be supplied and when to a selected crop.

A time-consuming and complex process is a precise estimation of the irrigation schedule [25]. However, the advent of advanced technology has made it simpler and the water supply can be scheduled precisely to meet the water requirements of cultivation. The timing for irrigation applications can be fixed dates or on flexible dates. The quantity should not exceed the crop requirements per application, including the leaching of salts; otherwise, any excess water would not only reduce the efficiency of its usage but can hinder the crop development. Standard irrigation schedule performance metrics are crop yields and net benefits per unit area.

The optimal irrigation schedule is any schedule that optimizes the adopted output measurement while meeting several defined constraints. Any schedule that optimizes the adopted measure of performance while satisfying some specified constraints is the optimal irrigation schedule.

4.1 Methods of Irrigation Scheduling

Different techniques can be apply to the plants with irrigation water and each approach has its benefits and limitations. In this context, the best approach to accommodate local conditions should be taken into account. Earlier, the primary irrigation method is applied via the source of supply such as a bucket watering or a well. Although, it is a time-consuming method.

More advanced water application methods are used in larger areas where irrigation is needed. The suitability of several irrigation methods, i.e. sprinkler, surface, or drip irrigation, depends on the following aspects: Natural conditions, type of crop, type of technology, previous experience with irrigation, required labor inputs and costs and benefits.

Surface irrigation may be categorized based on mode of water application as depicted in Fig. 5. [44] and Fig. 6 shown the different types of irrigation methods. Table 3 presented the different types of irrigation methods, advantages and their applications.

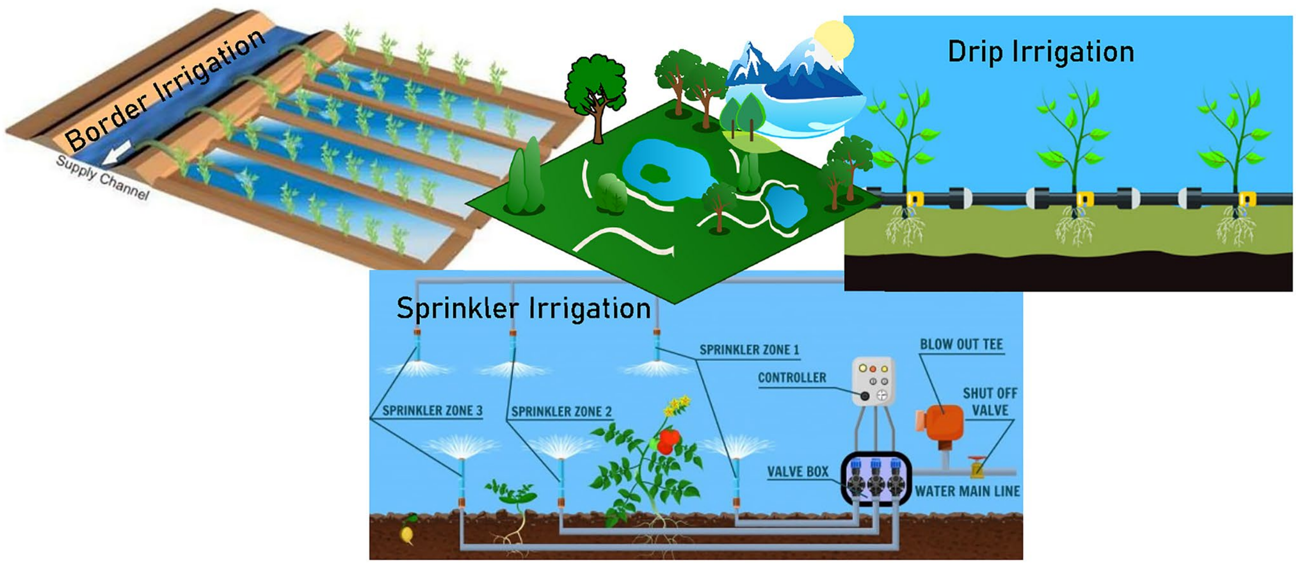

Fig. 5 Irrigation methods

Fig. 6 Types of irrigation scheduling

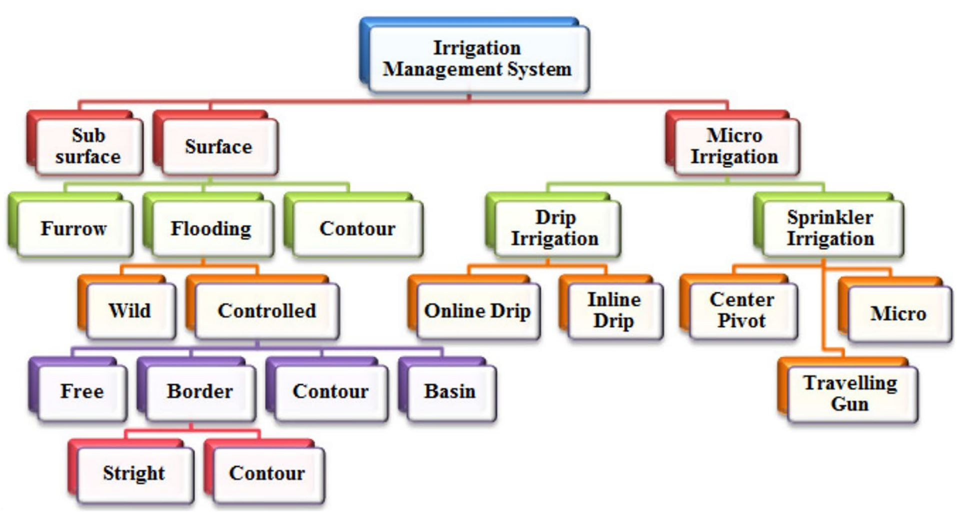

Table 3 Different types of irrigation systems

Name	Advantages	Application	Technology	Ref
Drip Irrigation	Efficient system, Saves water, Reduces nutrient leaching	Fuzzy Control for automatic greenhouse irrigation, DIDAS software for linearized water flow and scheduling	Matlab, Delphi (Embarcadero, Version XE3)	[45, 46]
Sprinkler Irrigation	Automatic Irrigation, Smooth fertigation and chemigation, No labor requirements	Multi-agent system for garden irrigation, Crop model AquaCrop for the optimization	Agent based simulation, AquaCrop Simulator	[47, 48]
Flood Irrigation	Usable on shallow soils, Low cost	The risk and sensitivity analysis of water, Energy and emissions in IR	Risk Software	[49]
Border Irrigation	Easy to design and maintain, Simple operations of the system, Natural drainage	Improved understanding of IR Models and measures basis for improving IR	SISCO	[50]
Furrow Irrigation	Accomplished, Minimal erosion , Adaptable to a large array of land slopes	Irrigation and fertigation in isolated furrow networks	C-language	[51]
Basin Irrigation	Small fields, Well suited for crops	Modelling and multi-criteria analysis of water saving	ISAREG, SRFR, SIRMOD	[52]

4.1.1 Border Irrigation

Surface irrigation is where the water is applied to the surface of field by gravity flow. The water is applied into small channels (furrows) or complete surface is flooded with water (basin irrigation) or strips of land (borders). Border irrigation is a modern method of surface irrigation. Borders are uniformly graded strips of land and long, set apart by earth bunds. They are also known as border strips. There are several ways to fed the irrigation water to the border such as by using small gates, launching the channel bank, using spiles or siphons. A sheet of water is guided by the earth bunds and flows down the slope of the border. It is mostly suited to generate long uninterrupted field lengths for facility of machine operations in the huge mechanized farms. Borders can be up to 3-30m wide and at least 800m in length depend on several factors. It is less applicable to farms on small-scale consisting animal-powered cultivation techniques or hand labor.

4.1.2 Sprinkler Irrigation

It is equivalent to natural rainfall, where water is pumped using a pipe system and then rotating sprinkler heads used to spray onto the crops. Further, the spray is applied into the air via sprinklers to breaks it into small drops of water that fall on the ground. The sprinklers, pump supply system, and operating conditions must be developed to apply the water uniformly. It is well suited for the most field, row, and tree crops. Water can be sprayed under or over the crop canopy. Although, large sprinklers are not suggested for delicate crops such as lettuce due to the large size water drops generated by the sprinklers can harm the crops.

4.1.3 Drip Irrigation

It involves application of dripping water to the soil from a small diameter plastic pipe systems attached with outlets called emitters or drippers at very low rates (2–20 l/h). It is also called as trickle irrigation. Water is applied very close to plants so that only part of the soil in which the roots grow is wetted, instead of sprinkler and surface irrigation, which consists wetting the complete soil profile [25]. It is well suited for trees, vine crops and row crops (vegetables, soft fruit), where one or more emitters can be given for each plant. It is considered for high-value crops only due to high capital costs required for installation of a drip system.

4.1.4 Need of Irrigation Scheduling

Hydrological, climatologist, and agronomical processes play an significant part in the development of irrigation agriculture production. These studies were mainly developed to estimate daily, weekly, or monthly evapotranspiration. The precise approximation of evapotranspiration is an important process that plays a key role in crop planning, deployment and production of irrigation systems.

In recent years, several approaches have been developed to overcome the problems and obstacles that occur with smart farming, such as species recognition, yield prediction, disease detection, drought, crop productivity problems and irrigation management.

So, there is a great need to explore more research studies to enhance the scalability of irrigation scheduling based on advanced data analytic and machine learning. Some research has been done in the decision support system to improve the right decision on agriculture data.

5 Decision Support System

The idea of a decision support system (DSS) for irrigation water management is introduced in the 1970's to assist users in complex decision- making processes and efficient use of irrigation water at the farm level [53].

Decision support system (DSS) has great potential in agriculture era, if the water irrigation management research is combined with the modeling approach using machine learning analytics and agriculture statistical, the research level will be achieved in different levels of the agricultural development sector. The decision support system for crop water irrigation scheduling based on crop water model by estimation of evapotranspiration as weather parameter, historical dataset, and using of different Irrigation water management methods.

The decision support system is an integrated approach to solve complex problems, combining the computer calculation and data storage capacities with human language and perception, support of mathematical model statistics, providing decision-maker. It is known as a primary tool in management for better decision making and environmental resources. In 1985, Guariso et al. firstly introduced the concept of DSS. Various researchers surveyed the advanced use of the management of DSS for water resources [54]. Today, it is required for the on-farm irrigation water management due to its use of the computer to relate soil, crop, and water quality conditions. It can be used for analyzing and determining how much water is needed and when it should give next time.

5.1 Statistics

The statistical approach leads to the process of collection, presentation, analyze, and apply the data to make decisions, problems solving, design products, and processes. It is very useful for us to explore the description and understand the variability. Statistical methods contributed for making scientific judgments in the face of variation uncertainty. Russo et al. (2015) Bayesian method is used to estimate the hydrological properties and irrigation needs for an under-constrained mass balance model. They presented an approach Markov chain Montecarlo algorithm to solve for spreading of values for each unknown parameter in a conceptual mass balance model [55].

5.2 Machine Learning

From the last decade, machine learning and data analytics is a hot-spot research area in the domain of agriculture. Among the other definitions, machine learning is described as the scientific are that allows the machines to learn without being strictly programmed [56].

Machine learning models have demonstrated excellent results for crop-based modeling in recent days. There is a variety of machine learning models based on prediction for reference crop evapotranspiration. The main contribution of our research prediction, by applying machine-learning and data analytics based modeling to predict crop evapotranspiration.

Yamaç and Todorovic [57], revealed the satisfactory outputs of ML with R2 ranged from 0.81 to 0.97 [58] by applying several ML models on the climatic data. A comparative analysis was performed by Shiri et al. [59] to estimate the ET_o using various intelligent models, namely ANN, ANFIS, support vector machine (SVM), and GEP. In the domain of agriculture, big data analytic technologies have offered newly predictive models for ET_o estimation, e.g. generalized neuro-fuzzy models [60], artificial neural network (ANN), [61], adaptive neuro-fuzzy inference system [62], multi-layer Perceptrons neural network (MLPNN), Zaji and Bonakdari [63], extreme learning machine (ELM) Abdullah et al. [64], multivariate adaptive regression splines (MARS) and least square support vector regression (LSSVM) [65], GRNN (2016), ELM, WNN and GANN [66]. Moreover, the Auto-ML technique is found to show excellence in application of irrigation scheduling where border irrigation and sprinkler irrigation methods are deployed.

5.3 Deep Learning

The deep learning technique is now practical to address millions or even billions of weights among neurons for better understanding of behaviors due to current advances in computational power, in terms of software, hardware and parallel processing. It is accepted to have established a revolutionary era since it can address the issues that have countered AI for a long time.

Deep feed-forward neural networks are based on multilayer Perceptrons (MLPs) published by Alexey Ivakhnenko and Lapa in 1965 [67]. It can be used to model the complicated relationship between input and output due of its high hierarchical structure model training, construction and feature learning [68]. It has been used in the hydrological and agricultural fields because of the difficulty of software data availability, costs, and complexity, e.g., approximation and modeling of crop evapotranspiration [42], Wang et al. (2018) determined that traditional ML and DL models are equivalent as a data-driven artificial intelligence method that can be used to model the complicated relationship between input and output [68]. However, DL has a benefit over traditional ML, due to wits high hierarchical structure model.

5.4 Big Data Analytics

Big Data is a fascinating new field at the joint of advanced analytics, data science, statistics, and machine learning. Big data and analytics have tremendous development benefits in the agriculture economy. Advanced big data analytics have improved the tools and technologies that changed the way of real-time applications to make better decision processing, high-performance platform to efficiently analyze, capturing, storing and managing large scale of big data. In addition, agriculture practices are becoming increasingly data-derived and data-enabled with the recent development of 5G, artificial intelligence, Internet of Things and big data technologies [69]. To obtain insights from these data Saggi et al. [70] investigated the state-of-the-art framework for decision-making and different methods of integrating big data analytical methods with smart applications such as smart agriculture, healthcare, and cyber security. Figure 7 presented the framework of big data analytics and machine learning analytics for agriculture application as follows:

- *Data sources* The domain of data is expressed by variety of descriptive terms such as:-structured, unstructured, machine and sensor generated data, batch, and real-time processing data, biometric data, human-generated data, and business-generated data.
- *Data storage and processing* Database technology, Storage infrastructure, Distributed storage, Programming model and Data staging, collection, pre-processing and many tools for batch and streaming process.
- *Data analytics and visualization* It includes the machine learning, data mining, statistics, artificial neural network, natural language processing, and deep learning models for agriculture based applications such as DSS, forecasting weather, crop-soil and water monitoring and pesticides detection.

The objective of this study is to introduced the several advanced analytic techniques to develop a flexible system that would lead to better irrigation decisions (allocation, application, and optimization). This study is expected to provide a decision tool that will assist irrigators and water managers in determining reference evapotranspiration (ET_o), crop water requirement (CWR), irrigation water requirement (IWR), and irrigation scheduling for more effective water allocation and application.

6 Literature of Irrigation Scheduling

Agriculture is the world's biggest water user, that consume 70% of fresh water in average. However, these percentages will go as high as 95 percent in few developed nations and

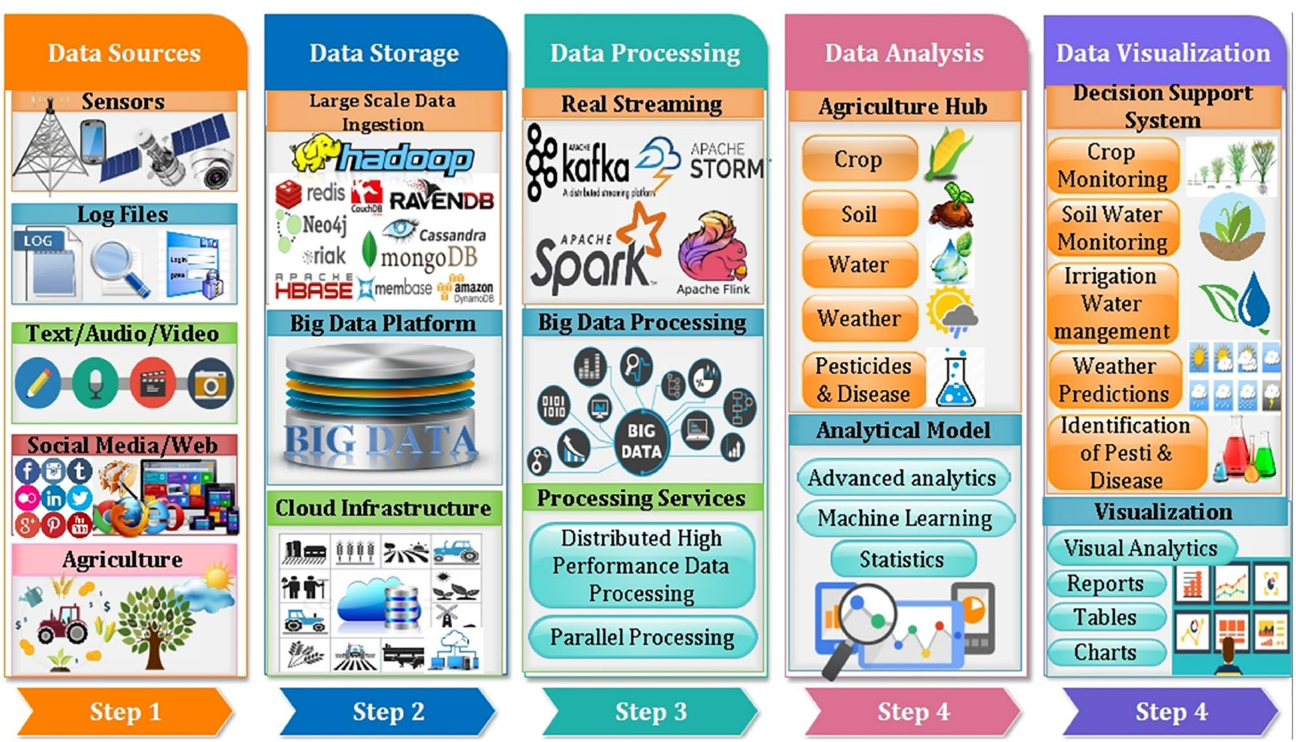

Fig. 7 Big data based machine learning framework for agriculture application

Punjab is one of India's largest contributors to the central grain pool. In India, ground-water (GW) is an essential source of water supply in agriculture and Rice-Wheat cropping system has resulted in significant increase in irrigation water need approximately 73% with GW in Punjab. India is a seventh largest subcontinent country by geographical area in South Asia, nowadays India ranks 2nd worldwide in farm production and 1st largest country in irrigated land area. Water conservation and precision agriculture is becoming a vital issue in the tropical climate areas. Central Indian Punjab is a well-known for its agriculture activities and occupied high percentage of land area in all over India.

6.1 A Bibliometric Perspective of Irrigation Scheduling

In this section, the articles from Science direct digital database is considered. Figure 8 shows the number of papers published from 1995 to 2021 in field of irrigation scheduling, reference evapotranspiration and crop evapotranspiration. We have selected only elsevier science direct library to find out research articles, where we found 34,083 results in area of irrigation scheduling, 32,775 papers in reference evapotranspiration and 14,261 results articles in crop evapotranspiration (crop water need).

Irrigation scheduling, ET_o and ET_c trends are represented by Green, Blue, and Yellow colored lines respectively. Figure 8 shows the article type in which review reports, case reports, data articles, mini review, and many more articles. Figure 8 shows the number of top-journal publications. Several computer simulation techniques and decision support systems have been developed to estimate ET_o, ET_c and Crop Water Requirement (CWR). It is important to identify changes in the hydrological cycle when we want to predict the impacts of climate change. However, current studies on climate change must be expanded to cover the entire globe. The two main components of the global water cycle are evaporation and precipitation.

Methods for measuring evapotranspiration from meteorological data include a number of climatology, and the physical inputs which is directly estimated in weather stations. Other parameters are associated with measured data and can be obtained by directly or empirical methods. Meteorological data can be expressed in several units.

6.2 Estimation and Forecasting of Evapotranspiration ET_o

The application of Evapotranspiration (ET_o) in irrigation scheduling is divided into different categories for literature section such as statistical, machine learning, evolutionary models, and decision support system [42, 71, 72]. We have presented a comprehensive review literature for reference evapotranspiration as follows:

Figure 9 presented the process of DSS for crop water irrigation scheduling. ET_o is an imperative aspect of the hydrological cycle that is stirring water availability on the earth surface. It is one of the significant criteria of accurate quantification of crop water requirement that influence various hydrological processes, planing of water management and resources [62], and requirement of irrigation [73]. Traditionally, the ET_o is estimated at the field scale, but it consumes lot of time and is difficult to process by complex mathematical calculations with various climatic variables. Methods for measuring evapotranspiration from meteorological data include a number of climatology, and the field inputs which is directly estimated in weather stations. Some parameters are associated with measured data, where as others can be obtained directly or through empirical methods.

6.2.1 Existing Methods Based on Empirical

Since many years, various researchers have established reference evapotranspiration ET_o estimation with empirical methods. There are few categories of ET_o estimation methods: Temperature-based, Radiation-based, Empirical, Pan, and many more. Commonly, FAO-56 Penman-Monteith method is applied as the scientific, standard and temperature based method to estimate the ET_o [10, 74]. FAO-PM has been extensively adopted because to its positive outcomes in a variety of climates across the world. However, it needs a significant amount of meteorological data obtained from regular meteorological observation stations [75].

To overcome the existing limitation of the FAO-PM model, various attempts aiming to estimate ET_o with limited observed data have been made. A large number of studies have focused on estimating ET_o using empirical methods with limited ground-level data such as the Hargreaves and Samani equation, Priestley-Taylor equation, and Thornthwaite equation have been used for estimating (ET_o) by Tomas-Burguera et al. [76].

ET_o is estimated with simplified or empirical methods (e.g. Lysimetric measurements) and it is highly difficult to achieve more precise and robust approaches [77, 78]. HS equation is the most simple and accurate approach based on temperature [10, 31]. There are many empirical approaches to predict the ET_o using five mass transfer-based models (Ivanov, WMO, Penman, Trabert, and Mahringer), five radiation-based approach (Tu, PT, Ab, JH, and Mk), and five temperature-based approach (HS, modified Hargreaves-Samani$_1$) (Th, BC, MHS_1, and MHS_2) [79]. Table 4 shows the literature of empirical methods for estimation of ET_o.

Malamos et al. [80] investigated the monthly Geo-spatial ET_o with FAO Penman–Monteith using line, polygon, and point through a geometry independent algorithm. They

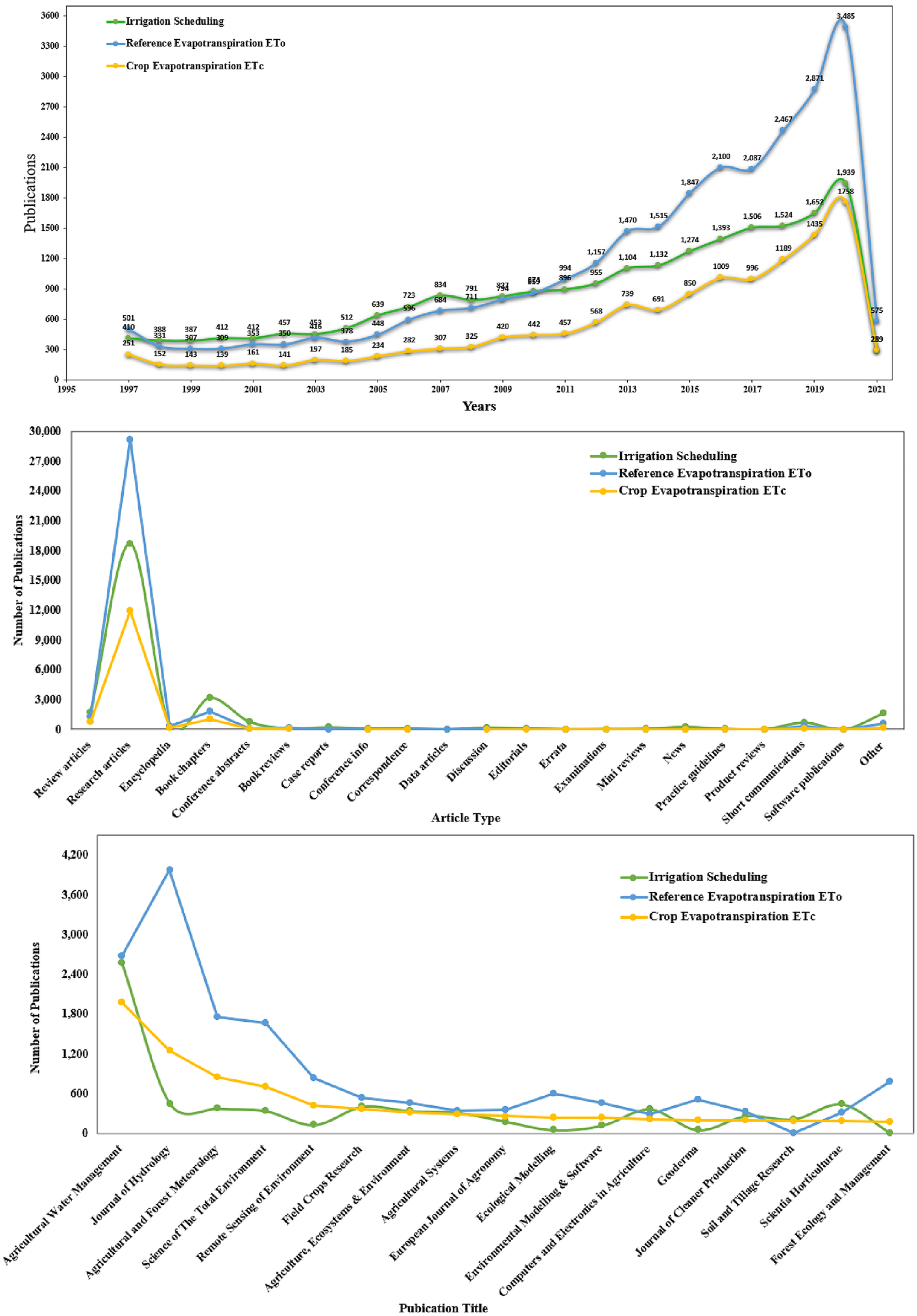

Fig. 8 Number of publications, article types and publication title

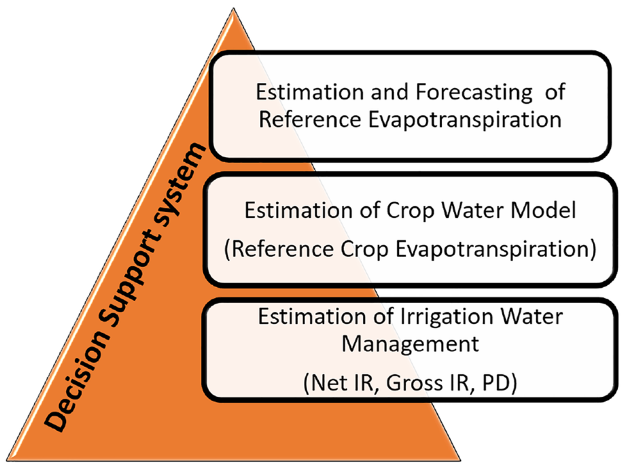

Fig. 9 Process of DSS for crop water irrigation scheduling

selected various climate parameters such as T_{mean}, u_2, R_H, latitude ϕ, altitude (m), I_s.

Tegos et al. [81] applied the radiation based model to calculate the daily potential evapotranspiration ET_o with FAO-56 Penman–Monteith using T_{mean}, u_2, R_H,and I_s parameters. The Potential ET_o is estimated for current and future drought condition using PDSI tool, Spatial, and Temperature based models such as Penman–Monteith, Thornthwaite, and Hamon methods. They have selected T_{mean}, u_2, R_H, I_s input variable, and analyzed on MATLAB GUI [82].

Yang et al. [83] analyses the daily reference evapotranspiration (ET_o) using short-term forecasting with FAO-56 Penman–Monteith equation, Hargreaves–Samani equation, and Reduced-set Penman–Monteith (RPM). The R language is used to simulate with various climate parameters including T_{mean}, T_{max}, T_{min}, u_2, RH_{mean}, I_s, and Vapor pressure (ea).

6.2.2 Existing Methods Based on Machine Learning

There have been many studies on hybrid models with machine learning, and evolutionary algorithms to estimation of ET_o with few climate parameters around the world.

Patil and Deka [85] investigated the performance of extreme machine learning (ELM) to quantify the weekly ET_o in the Thar Desert of India. Also, they have showed the comparison of Artificial Neural Network (ANN) with three input variable. The ELM model gives slightly higher accuracy than empirical, and ANN models.

Wu et al. [86] proposed hybrid model using machine learning and soft-computing to estimate the monthly ET_o in south China with 26 data stations. The proposed (Kmeans-FFA-KELM) approach developed with the three approaches (K-means clustering, Firefly Algorithms, and Kernel Extreme Learning Machine model) found higher accuracy using three input variables ($Temperature_{max}$, $Temperature_{min}$, and R_a). Another study showed performance of six remote-sensing based ML models to predict the daily ET_o in the Andalusian. The two ELM and MLP models found higher accuracy than RF, SVM, GRNN, and XGBoost models [87].

Stacking and blending ensemble based ML models are used to calculate the daily ET_o with limited input variables. Two-layer ensemble model is build with RF, SVR, MLP, LR and KNN models and found higher accuracy in terms of R^2 ranged from (0.66 to 0.99) as compared to empirical models [88]. Another, ensemble based model is build with ANN, SVM and RF to estimate the ET_o with geno-types and optimize the ET_o with time series data, and found the correct results [89].

Bai et al. [90] proposed ensemble-based four ML models with RF, BMA, KNN, SVM and MLP to calculate the ET_o. The MLP-based ensemble model provides the efficient results. However, the ML and DL based models are proposed to estimate a urban ET_o with Flux Footprint, Remote Sensing and Geographic Information System (GIS) data. The RF model provides slightly better result in terms of R^2 of (0.840) and RMSE of (0.0239 mm) than CNN model [91].

Adnan et al. [92] demonstrated the capability of different Neuro-Fuzzy methods to estimate the pan evaporation monthly using climatic inputs of different parameters obtained from Uttarakhand, (India). Recently, Adnan et al. [93] demonstrated the capability of dynamic evolving Neural-Fuzzy Inference System (DENFIS) and Least-Square Support Vector Regression with a Gravitational Search Algorithm (LSSVR-GSA) for estimating ET_o.

It has been shown that the extraterrestrial radiation or temperature-based LSSVR-GSA models are superior to

Table 4 Estimation of evapotranspiration ET_o with empirical methods

Author	Method	Parameters
Malamos et al. [80]	FAO Penman–Monteith	T_{mean}, u_2, R_H, latitude ϕ, altitude (m), I_s
Tegos et al. [81]	FAO Penman–Monteith	T_{mean}, u_2, R_H,I_s, R_s, R
Ficklin et al. [82]	Penman, Monteith, Thornthwaite, Hamon	T_{mean}, u_2, R_H,I_s
Yang et al. [83]	FAO-56 Penman–Monteith, Hargreaves–Samani, Reduced-set Penman Monteith (RPM)	T_{mean}, T_{max}, T_{min}, RH_{mean}, u_2, I_s, VPD.
Heydari et al. [84]	Blaney-Criddle	T_{mean}, RH_{min}, u_2, I_s, ρ, α, and β coefficients.

DENFIS model for estimating monthly ET_o. They [94] forecasted the monthly and daily stream flows of poorly gauged mountainous watershed with Fuzzy Genetic Algorithm (FGA), Least Square Support Vector Machine (LSSVM), and M5 model tree (M5T) models.

Heddam et al. [95] estimated and compared daily reference evapotranspiration (ET_o) using the Online Sequential Extreme Learning Machine (OSELM) and Optimally Pruned Extreme Learning Machine (OPELM) in the Mediterranean region of Algeria. The OPELM models showed good performances as compared to OSELM models.

Recently, Tikhamarine et al. [96] combined the Support Vector Regression and Grey Wolf Optimizer (SVR-GWO) to predict the monthly ET_o at Annaba, Algiers, and Tlemcen stations in North Algeria. Moreover, the proposed model is compared with the existing variants of SVR and showed that the performance of the SVR-GWO gives occasionally competitive and very promising results. Maroufpoorb et al. [34] proposed the concept of hybrid Artificial Neural Network-Gray Wolf Optimization (ANN-GWO) model and predicted the ET_o for Iran.

Further, the proposed model showed more efficient and accurate results as compared to ANN and LS-SVR. Mohammadi and Mehdizadeh [97] proposed a hybrid of two models Support Vector Regression and Whale Optimization Algorithm to predict the daily reference evapotranspiration at three stations in Iran. It has been shown that hybrid models outperformed the support vector regressions models. Kisi [65] obtained weather dataset from Turkish Meteorological Organization (TMO) for 2 stations from 1982 to 2006 and applied MARS, LSSVR, and M5-Tree to estimate ET_o.

Valipour et al. [79] collected data for the period of (1961–2010) with 50 climate parameters from 18 regions of Iran to estimate monthly ET_o using five models namely (mass transfer, radiation and temperature based).

Mattar [98] obtained 32 weather stations of data from United Nations Food & Agriculture Organization (UN-FAO) known as CLIMWAT for (2013 to 2015) and presented gene expression programming (GEP) and empirical models to estimate ET_o.

Tao [99] presented the hybrid intelligent ET_o model using data of three meteorological stations during 1998 to 2012. They used the Adaptive Neuron Fuzzy Inference System (ANFIS), Firefly Optimization Algorithm with ANFIS (ANFIS-FA) and Penman–Monteith models.

Co-active Neuro Fuzzy Inference System (CANFIS) model is proposed for modeling the monthly evaporation of Lake Nasser, Egypt [110]. The Gene Expression Programming (GEP), Support Vector Machine (SVM), Classification and Regression Tree (CART), the Cascade Correlation Neural Network (CCNNs), and are proposed for estimating evaporation by Yaseen et al. [100].

Falamarzi et al. [101] estimated the daily ET_o for water resources with ANN and WNN models from the period of 2009 to 2012. They have applied RMSE, APE, N.S., R^2 metrics to check the model accuracy with three input parameters such as T_{min}, T_{max}, and u_2. Models LS-SVM, MARS, and M5 models have been applied to estimate the Pan evaporation for Reservoir and water resources management. They have applied four input variable, T_{mean}, R_s, u_2, and R_h with dataset of period 1986 to 2006 [102]. Another, ANN model is applied to forecast the ET_o for application of real-time irrigation scheduling with T_{mean}, R_s, u_2, and R_h input parameters using dataset of (2011 to 2012) [103].

Yassin et al. [73] analyzed the performance of ANN, and GEP models to quantify the ET_o with various climate parameters using dataset from 1980 to 2010. The GeneXpro Tools 5.0, and Propagation version 2.2.4 were used to developed the model and also provide the accuracy on the basis of these metrics MAE, RMSE, R^2, and OI. Gocic et al. [71] forecasted the ET_o using SVM, FFA, DWT, ANN, and GEP models with climate parameters for the period of 1980 to 2010. Goyal et al. [104] explored the four ML models namely ANN, LS-SVR, FL, ANFIS, and Gamma Test to estimate the pan evaporation for the duration of 2000 to 2010. They have found the efficient results with the FG and LS-SVR models using various climate parameters on MATLAB platform.

However, Chen et al. [105] found the best performance of Bayesian Model Averaging Model to estimate the terrestrial ET_o using KGE and Cubist software. Mehdizadeh et al. [106] proposed the hybrid model to estimate the monthly ET_o with GEP, SVM-Poly, SVM-RBF, and MARS models for duration of 1951 to 2010. The performance of the applied models is compared with the empirical methods, where the MARS and SVM-RBF models give the most accurate results. The hybrid ELM model revealed a superior performance to estimate the daily ET_o at the four major countries of (US, Germany, Belgium, and Sweden) using 9 years of dataset [72].

Mohammadi et al. [97] proposed an approach that couples Support Vector Regression with Whale Optimization (SVM-WO) to estimate the daily ET_o.The T_{max}, T_{min}, RH_{mean}, u_2, R_h, and SSD parameters are used to build the model and found accurate result with SVM-WO model.

The recent estimation of reference evapotranspiration based on machine learning modeling, e.g. H2O-Deep Learning,Distributed Random Forest,Gradient Boosting Machine and Generalized Linear Model [107], Ensemble Extreme Machine Learning, Multi-layer Perceptrons-Neural Network, Support Vector Machine [108], Quantum Matrix Product State [111], CNN-LSTM and Conv-LSTM used for combine the features and modeling of ET_o [109], Deep learning versus gradient boosting used for predicting the pan evaporation [112], In the domain of agriculture, ML offered new predictive models for ET_o estimation, e.g. Generalized Neuro-Fuzzy Models (GNFM) [60], ANN model [61], ANFIS model [62], MLP-NN [63] [113], ELM algorithm [64] [90], M5 Model Tree [113], LS-SVR , MARS, ELM, WNN and GANN [66]. The DL model and ML model are applied in various domains such the COVID-19 analysis [114], proposed a novel method based on artificial intelligence (AI) to identify COVID-19 disease [115], developed genetically optimized Deep Neural Network [116], Tripathy et al. [117] investigated the performance of MARPUF approach and it is found to be better resistant to such modelling attacks, image classification using deep learning [118], Artificial Intelligence approaches used to classifying various types of cancer [119], enhanced the grip functionality of myoelectric hands based on deep learning [120], and classifiers for on-line handwriting recognition based on SVM and KNN algorithms [121], and a survey for software fault prediction [122]. Singh et al. [123] presented the efficient results and reliable algorithm for optimal design of water distribution

Table 5 Estimation of evapotranspiration ET_o based on ML and EA

Author	Purpose	Algorithm	Data	Parameters
Patil and Deka [85]	Weekly ET_o	ANN, ELM	T_R(1970–2005) T_S(2006–2010)	T_{max}, T_{min}, RH_{max}, RH_{min}, R_s, u_2
Wu et al. [86]	Monthly ET_o	Kmeans-FFA-KELM	T_R(1966–2000) T_S(2001–2015)	T_{max}, T_{min} ,R_a
Wu [88]	Daily ET_o	ELM, MLP, RF, SVR, GRNN, XGBoost	T_R(1989–2008) T_S(2009–2018)	T_{max}, T_{min}, RH_{mean}, R_a
Bai et al. [90]	Daily ET_o	RF, KNN, SVM, MLP	FLUXNET 2015 47 cropland	T_{mean} R_n, u_2, NDVI, EVI, VPD, DTsR, TR, Pd, and WSF
Adnan et al. [93]	Monthly ET_o	DENFIS, LSSVR-GSA	T_R(1961–1986) T_S(2000–2012)	T_{mean} R_a
Heddam et al. [95]	Daily ET_o	OSELM, OPELM	T_R(2001–2008) T_S(2009-2013)	T_{max}, T_{min}, RH_{mean}, R_s, u_2
Tikhamarine et al. [96]	Monthly ET_o	SVR-GWO, SVR-PSO	T_R(2000–2009) T_S(2009–2013)	T_{max}, T_{min}, RH_{mean}, R_s, u_2
Maroufpoorb et al. [34]	Daily ET_o	ANN-GWO, LS-SVR	T_R(2012–2016) T_S(2017)	T_{max}, T_{min}, RH_{mean}, S_h, u_2, P_e
Kisi [65]	Monthly ET_o	LS-SVR, MARS, M5 Tree	1982–2006	T_{mean}, RH_{mean}, S_h, u_2, R_s
Mattar [98]	Monthly ET_o	GEP	2013 to 2015	T_{max}, T_{min}, RH_{mean}, S_h, u_2
Tao (2018) [99]	Monthly ET_o	ANFIS, ANFIS-FA, Penman–Monteith	1998–2012	T_{max}, T_{min}, RH_{max}, u_2, R_s, VPD
Yaseen et al. [100]	Evaporation	CART, CCNN, GEP, SVM	1999 to 2009	T_{max}, T_{min}, RH_{mean}, u_2, S_h, RF
Falamarzi et al. [101]	Daily ET_o	ANN WNN	2009–2012	T_{min}, T_{max}, u_2
Kisi [102]	Pan Evaporation	LS-SVM MARS M5 Tree	1986–2006	T_{mean}, R_s, u_2, R_h
Ballesteros et al. [103]	Forecasting ET_o	ANN	2011–2012	T_{mean}, R_s, u_2, R_h
Yassin et al. [73]	ET_o	ANN, GEP	1980–2010	T_{mean},T_{max}, T_{min}, RH_{mean}, RH_{max}, RH_{min}, u_2
Gocic et al. [71]	Forecasting ET_o	SVM, FA, DWT, GEP	1980–2010	T_{max}, T_{min}, e_a, u_2, I_s
Goyal et al. [104]	Daily Pan Evaporation	ANN, ANFIS, LS-SVR, FL	2000–2010	R_r, T_{max}, T_{min}, RH_{max}, RH_{min}, I_s
Chen et al. [105]	Terrestrial ET_o	BMAM	1982–2009	T_{mean}, T_{max}, T_{min}, RH_{mean}, u_2, R_s, R_n, VPD
Mehdizadeh et al. [106]	Montly ET_o	GEP, SVM-Poly, SVM-RBF, MARS	1951–2010	T_{mean}, T_{max}, T_{min}, RH_{mean}, u_2, R_s
Dou et al. [72]	Daily ET_o	ELM, ANN, SVM, ANFIS	2001–2009	T_{max}, RH_{mean}, R_{net}, T_{soil}
Saggi et al. [107]	Daily ET_o	H2O- DL, RF, GBM, GLM	ST_1 (1978–1999& 2007 -2016) ST_2 (1970–1999 & 2007–2016)	T_{max}, T_{min}, RH_{mean}, I_s, R_s, u_2
Saggi et al. [108]	Daily ET_o	ELM, MLP, SVM	T_R (1970–1990), V_L (1993–1999), T_S (2007–2016)	T_{max}, T_{min}, RH_{mean}, I_s, R_s, u_2
Sharma et al. [109]	Daily ET_o	CNN-LSTM and Conv-LSTM	ST_1 (2003 to 2015) & ST_2 (2000 to 2016)	T_{max}, T_{min}, RH_{mean}, I_s, V_p, R_s, u_2

networks.The literature summary of ML and EA are given in Table 5.

7 Estimation of Crop Evapotranspiration (ET_c)

Crop evapotranspiration (ET_c) one the most essential element of the hydrological system for irrigation scheduling. The crop coefficient K_c method multiplied with (ET_o) is most widely-used to determine the (ET_c) Eq. (3). Different estimations and methods having their own advantages and disadvantages are available. For the estimation of ET_c using Machine Learning, Deep Learning and Evolutionary Algorithms, some potential literature work are presented in this section. The literature analysis of crop evapotranspiration methods is presented in Table 6.

7.1 Existing Methods Based on Statistics

The need of precise estimation of crop water is an crucial aspect of agricultural planning and there exists several methods for determining ET in crop land [124]. The significant field based estimations are required, appropriate for monitoring the crop-water status at the land-scale level [125, 126].

The FAO-Penman, PM, and 1963 Penman applied to forecasting the ET for rice crop using meteorological data by Shah and Edling (2000). They have found the crop coefficients for initial, middle and late stage as 1.39, 1.51, and 1.43 [127]. The derivation and development of crop K_c were identified for Castor and Maize crops of Rajendranganagar by Reddy et al. [128]. Ko et al. [129] conducted study to estimate the crop water requirement for Cotton and Wheat crops at Uvalde, TX, USA. Fang and Ping (2013) presented an optimal the uncertainty approaches of interval regression analysis and crop water production function for irrigation and Penman-Monteith method used to obtain ET_o. LINGO software introduced to solve above model [57].

Table 6 Estimation of ET_c based on empirical, ML and EA

Author	Algorithm	Crops
Han et al. [130]	BP-NN	Wheat
Mehta et al. [131]	Empirical	Wheat, Maize
Saggi et al. [41]	Fuzzy-Genetic and Regularization Random Forest	Wheat, Maize
Elbeltagi et al. [132]	DL	Wheat
Russo et al. [55]	Bayesian, MCMC	Rice
Ehret et al. [133]	NN, RA	Tomato
Maurya et al. [134]	Fuzzy-based, Hybrid routing	Maize
Yang et al. [135]	Fuzzy Inference Model	Wheat Corn, Cotton
Chauhan et al. [136]	DSS	Peanut
Gavilán et al. [137]	Radiation, Makkink FAO-24	Strawberry
Tabari et al. [138]	ANFIS, SVM	Potato
Yamaç et al. [139]	NN, ABM, KNN	Potato

7.2 Machine Learning and Evolutionary Models

The Back-propagation Neural Network (BP-NN) model is proposed to evaluate the crop evapotranspiration ET_c with combination of various climate parameters (T_{max}, T_{min}, RH_{mean}, S_h, RF and crop coefficient K_c). It is observed that the combination of Eddy Covariance method and BP model achieved the best accuracy in terms of R^2 (0.87) and accuracy (91.44%) than MLR model [130]. Mehta et al. [131] estimated the ET_o, ET_c and K_c of Wheat and Maize crops of Gujarat using climate data. They applied the various temperature and radiation based empirical methods to calculate and estimate the crop water requirement.

It is observed that the accurate value of K_c for Wheat crop is more efficient as compared to FAO-56 Penman–Monteith method results. Whereas in case of maize crop the outcomes were found less accurate at Surat and higher outcomes as compared to FAO method at Bharuch station.

Saggi et al. [41] proposed a novel multi-layer ensemble model based on fuzzy-genetic and regularization random forest (FG-RRF) for predicting the K_c and ET_c of Ludhiana station. They found that the models had high performance for modeling K_c and ET_c.

Elbeltagi et al. [132] presented the deep learning model to estimate the Wheat ET_c from 1970-2017 and forecasting the future changes from 2022-2035 of Nile Delta in Egypt using Visual Gene Developer technology. For calibration R^2 of 0.95, 0.96, 0.97 and for testing R^2 of 0.94, 0.95, 0.95 have been found efficient result respectively. Russo et al. [55] presented the MCMC and Bayesian algorithms to analysis the irrigation requirements for ground water mass balance with soil tensiometer of Rice crop. They have optimized the management decisions on crop replacement and increased the irrigation efficiency. The NN model and regression model are explored to estimate a greenhouse tomato crop yield, its growth, and efficiency in use of water with CropAssist and NeuralWare platforms [133]. Maurya et al. [134] developed a novel fuzzy-based energy-efficient routing protocol based on automated irrigation system for Maize crop on MATLAB platform. The FIS-DSS (Flexible Irrigation Scheduling Decision Support System) is proposed to analyze the optimal allocation of water resources of irrigation system. Fuzzy-inference and knowledge based user-friendly optimization tool is developed for Wheat and corn crops [135]. Chauhan et al. [136] proposed a web-based DSS to enhance irrigation water management for peanut crop on APSIM platform.

Gavilán et al. [137] measured the daily greenhouse crop evapotranspiration for strawberry and found more accuracy using empirical methods and sensors based on soil moisture. Tabari et al. [138] explored a ANFIS and SVM model performance for Potato crop evapotranspiration ET_c using meteorological data.

Yamaç et al. [139] applied the four scenarios based on features subset to accurately estimate the ET_c of Potato crop using ANN, ABM and KNN models. Further, ANN and SVM models are also applied to estimate the garlic ET_c by Abyaneh et al. [140] and the outcomes are found accurate as compared to lysimeter performance.

The need of precise estimation of crop water is an crucial aspect of agricultural planning and there exists several methods for determining ET in crop land [124]. The field based estimations are required and appropriate for monitoring the crop-water status at the land-scale level [125] [126].

The FAO-Penman and Penman methods are applied to forecast the ET for rice crop using meteorological data [127]. They have found the crop coefficients for initial, middle and late stage as 1.39, 1.51, and 1.43. The derivation and development of crop K_c are identified for Castor and Maize crops of Rajendranganagar by Reddy et al. [128]. Ko et al. [129] conducted a analyses report to evaluate the crop water requirement for Cotton, and Wheat crops at Uvalde, TX, USA. Fang and Ping [57] presented an optimal solution to estimate the ET_o using interval regression analysis, crop water production function and Penman-Monteith method with LINGO software.

Numerous experiments have been conducted in recent decades to investigate the possible effect of climate change on evapotranspiration ET_c. For efficient crop evapotranspiration ET_c modeling using VIP (Vegetation Interface Processes) for Wheat and Maize [141], durum Wheat in Tunisia [142], APSIM-Maize model [143], SEBAL model for yield, WUE, IWUE and HUE for Wheat crop [144], weighing lysimeter for K_c and ET_c [145], farm-level operational services in smart agriculture [146], crop water model based on Crop2ML framework [147] have been used.

The ET_c estimation results proved that the ML and EA approaches performed better than existing classical methods. However, several studies have investigated the estimation of ET_c with empirical methods. But limited studies have reported the estimation of ET_c using ML, and EA models as shown in Table 6.

8 Decision Support System for Irrigation Scheduling

This section considers the Decision support system (DSS) based on research that have included ET_o, ET_c, and irrigation requirement. An irrigation management system can offer farmers with appropriate decision-making tools in order to regulate the amount of water supplied to crops.

A decision support system PETP V2.0.0 is developed to analysis and estimate the potential evapotranspiration ET_o using various empirical approaches namely Hargreaves, Jensen-Haise, Penman-Monteith, Priestley-Taylor, etc. Visual Studio 2010 software is used to build the computational tool to estimate the accurate results for water requirement of crop [148].

Navarro et al. [149] developed smart irrigation DSS for managing the irrigation scheduling. They purposed 2 ML techniques i.e. PLSR and ANFIS. Maximum and minimum relative humidity, temperature, and direction of wind, global radiation, vapour pressure deficit, rainfall, dew point are the variables used to predict the daily ET_o with FAO Penman–Monteith method. Zizhong and Zenghui [150] presented a single irrigation system that enhanced higher corn production and also provided efficiency in use of water in Northeast China. They include climate parameters namely average, max and min of air temperatures, max and min of relative humidity, wind speed, and sunshine hours from 1980 to 2012. Penman–Monteith approach is used to determine the soil evaporation and ET_c.

The knowledge of the irrigation management has an impact on crop water requirements, maintaining water balance and is the practical considerations to enhance productivity of crop [157]. Various research work in Punjab have demonstrated the requirements of crop water irrigation, irrigation water based on ET and pan evaporation, [158], but few studies have focused on Soil Water Deficit (SWD) [159].

Paraskevopoulos and Singels [151] investigated the integrated content of soil water recordings of real-time field into the MyCanesim system to estimate its use in 15 sugarcane fields of South Africa for supporting irrigation system. It is used to determine the decision making for irrigation scheduling based on the status of forecasts of crop, soil water, and the next irrigation date. Ying et al. [152] represented the evaluation for summer Wheat and winter Maize cropping system for optimal irrigation scheduling. Further, they described topical versions of the SWAP and Wofost models for crop growing simulation and obtaining efficiency in use of water.

Afzal et al. [160] improved water resources management using different irrigation strategies and water qualities by field, and modeling study. To deficit irrigation PRD and RDI methods are used to estimate the effects of waste and fresh water on salinity distribution, soil moisture, and crop yield of Potato, Maize in Italy, Bologna through field experiments.

The fuzzy, evolutionary, and machine learning models are used to develop a DSS model for irrigation scheduling. Gaiqiang et al. [135] developed a FIS-DSS software based on knowledge, interface for user, and an inference engine for wheat, corn and cotton crops. It is a fuzzy interval programming model having multiple objectives and constraints, flexibility of model, data processing, and an alternative solving algorithm. The main objective is to maximize the economic-based benefits for crop-land in China. The NN model is used to train the model with precipitation and historical climate parameters.

Giusti and Marsili-Libelli [153] developed a fuzzy-DSS to schedule the daily irrigation need of crop based on soil moisture as a predictive model and an inference model as irrigation decision maker. This model determines the actual need of water for kiwi, corn, and potato crops with past irrigation soil moisture, climatic parameters, and ET_c. They used meteorological data including temperature, solar radiation, wind, rain, etc. The objective of FDSS model is to reduce the water usage and provide the efficient result in terms of saving water up-to 13.55, 18.3, and 72.95 water units for irrigating three crops respectively. Sahoo et al. [161] proposed fuzzy multi objective linear programming approach for planing of land-water-crop system. The meteorological data like daily rainfall, evaporation, temperature, solar radiation, daily sunshine hours, humidity, wind velocity, and albedo are collected from the Central Rice Research Institute, Cuttack. The objective function is to optimize, maximized crop production, net return, and to minimize the labor requirement for various vegetables and pulses.

Reddy and Kumar [162] demonstrated a multi-objective method for the optimal crop pattern and multi-crop irrigation reservoir scheme by several procedures. Adeyemo and Otieno [163] explored a method to solve the multi objective crop planning model by an evolutionary algorithm. They have found excellent results in minimizing total water irrigation, maximizing the yield productivity, and net income from farming.

Irrigation water management is numerically intensive for computations and provides model interpretation and discretization. Neural networks and evolutionary algorithms demonstrated to estimate the irrigation volume and also determined the effectiveness to diminish irrigation application and maximize production [164]. Ortega Álvarez et al. [154] proposed a non-linear model to recognize yield schemes and water irrigation management plannings using the genetic algorithms. Further, they estimated crop yield, gross margin and production as a function of irrigation depth. Schmitz et al. [165] simulated 92 percent greater production for corn using evolutionary algorithm as compared to dynamic programming.

Application and web based DSS models are developed for the irrigation water scheduling by various researchers. Recently, a web-based DSS is proposed to estimate the soil-water balance for irrigation system with limited input parameters such as (dual crop-coefficient and meteorological). The irrigation parameters are computed through soil moisture and requirement of water. A web-based irrigation decision support system is introduced with limited inputs (WIDSSLI) for summer corn and winter Wheat irrigation management in North China Plain (NCP) [155].

Table 7 presents the estimation of ET_o, ET_c, and irrigation with DSS systems. Antonopoulou et al. [166] presented an appropriate decision support system for crops which is implemented on web-based software. They introduced this approach by using the Java and PHP technologies for specific irrigation technique and soil improvement instructions. Dutta et al. [167] developed a mobile application based on sustainable irrigation DSS. They proposed cloud sensors based approach to evaluate the ground water usage and availability of water. This approach includes the CSIRO sensor based cloud computing organization and integrated big data that includes machine learning technologies. Bonfante et al. [168] proposed an irrigation water supply management tool to obtain the maximum yield of Maize with W-tens, IRRISAT, and W-Mod approaches. W-Mod and IRRISAT models found more accurate results as compared to W-Tens in terms of irrigation water use efficiency.

A Climate-Smart Decision-Support System (CSDSS) tool is proposed to evaluate the requirement of rice crop in Malaysia. They determine a daily crop-water balance based

Table 7 Estimation of evapotranspiration ET_o, ET_c, and Irrigation with DSS systems

Author	Estimation	Developed Software	Approach	Crop
Cesar et al. [148]	ET_o	PETP V2.0.0	Empirical Methods	–
Navarro-Hellín et al. [149]	ET_o, IR	DSS	PLSR, ANFIS	–
AL et al. [151]	IR	MyCanesim	–	15 Sugarcane
Ma et al. [152]	Optimal IR	DSS	SWAP, Wofost	Summer Wheat, Winter Maize
Yang et al. [135]	Crop-land Model	FIS-DSS	Fuzzy Interval Programming, Neural Network	Wheat, Corn, Cotton
Giusti et al. [153]	ET_c, IR	fuzzy-DSS	Fuzzy	Kiwi, Corn, Potato
Alvarez et al. [154]	Yield, Gross margin	Non-linear Model	Genetic Algorithms	
Li et al. [155]	Soil-water balance IR	Web-based DSS	Dual crop-coefficient	Summer Corn, Winter Wheat
Rowshon et al. [156]	ET_c	Climate-Smart-DSS	GCM	Rice

on input data (2010 to 2099) and (1976 to 2005) from Global climate models (GCM) and integrate with evapotranspiration using MATLAB simulator [156].

Ragab et al. [169] proposed a SALTMED model which includes the to partial root drying or deficit irrigation, subsurface irrigation, soil nitrogen fertilizer application, fertigation, dry matter production, plant nitrogen uptake, and nitrate leaching.

For the model calibration and endorsement the statistical measurements are used such as R2 coefficient, RMSE, and percentage error. The DIDAS software package for irrigation system decision-making strategies of drip irrigation systems is developed [46].

A DSS framework have been introduced which includes 22 ET_o estimation approaches using user-friendly GUI (Microsoft Visual Basic 6.0) of 133 selected stations of India [170]. Potential-ET_o and FAO56-PM ET_o are used to estimate the ET_o in the Geisenheim Irrigation Scheduling (GS) for vegetable crops using sprinkler irrigation [171]. Ballesteros et al. [103] estimated the ET_o using FORETO software with Hargreaves Samani (HS) equation or the Penman Monteith (PM) and Artificial neural networks (ANNs) models. Modern platforms (.NET and Java) software applied to calculate the daily/monthly ET_o using meteorological parameters [172]. There are various crop simulation based models exists such as CropSyst [173], STICS (Brisson et al. 1998) [174], EPIC [175], DSSAT [176], VegSyst simulation model [177], and CERES [178].

A single approach, that can address all operational circumstances (weather information, crop growth monitoring, field data, agricultural expertise and infrastructure etc.), as well as the associated expenses for farmers which may limit the usage of these systems. Therefore, DSS's for irrigation scheduling have been developed to integrating various approaches in terms of (data collection from meteorological), pre-processing techniques and modeling based on empirical or artificial intelligence.

9 Conclusion

Overall agricultural systems modeling needs to rapidly adopt and absorb state-of-the-art data and ICT technologies with a focus on the needs of beneficiaries and on facilitating those who develop applications of their models. In spite of the vast literature available, the subject of irrigation water management and crop water modeling for machine learning techniques are yet in its emerging phase. Although there is wide literature available on statistics, machine learning, decision support system for general manifolds. To estimate crop water modeling on general manifolds, we have different approaches available in literature.

Moreover, the water balance is well-entrenched approach for estimating irrigation amount and time (i.e. irrigation frequency) in irrigation scheduling. This approach is simple to use, typically inexpensive and very effective approach to estimates the ET_o, and ET_c. The major objective is to adopt the several approaches to develop a flexible system that supports irrigation water requirement system, which may fit into diverse fields of operational activities (weather information, field data collection, crop coefficients etc.). This study provides an overview of the irrigation water scheduling. It also presented the concept of reference evapotranspiration and crop evapotranspiration for crop water modeling. It also presents the various methods of irrigation scheduling. It also address the need of decision support system and its various approaches that lead to irrigation water management.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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