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Irrigation Practices and Soft Computing Applications: A Review

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Abstract

Repeated droughts, population expansion and global warming force thorough limitations on irrigation practices. The low water usage efficiency is the universal problem encountered by most of the irrigation systems. A survey was carried out over irrigation practices, which comprises of conventional irrigation methods, micro-irrigation systems, intelligent irrigation approaches, estimation of reference evapotranspiration (ET_0) using soft computing models and performance indicator models. The outcome of the survey reveals that, the software techniques must be integrated with traditional irrigation practices to improve water productivity and economy.

Key words: Irrigation methods; Land suitability; Machine learning; Performance indicators.

1. Introduction

Economic progress and expanding worldwide populace extend the interest for innovative irrigation system. According to the expectation of food and agriculture organization (FAO), food necessity will increment about 60% by year 2050 (Alexandratos and Bruinsma, 2012). Internationally, evaluated that agriculture action devours around 70% of the gross water, grouped with 10% for civic use and remaining water is used by mechanical sector (Provenzano and Sinobas, 2014). Worldwide, inundated land represents 302Mha and possesses just 16% of the cultivatable region (Playan *et al.*, 2013). Presently, 36% of land by bone-dry and semi-parched locales and anticipated that drought risk will further increment (Safriel *et al*., 2006; Alcamo *et al*., 2007; Arnell *et al*., 2011). The water productivity (WP) is the proportion between crop yield and complete water use (Pereira *et al*., 2002). The water devoured by plants is under 65% of provided water and right volume of plants upon right time improves the WP (Chartzoulakis *et al*., 2015). The design of effective irrigation system is complex because of barometrical conditions, soil properties, crop species and irrigation strategy (Dabach *et al*., 2013; Soulis and Elmaloglou, 2018). The generally

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utilized irrigation system strategies are surface, pressurized sprinkler, low volume drip and micro-sprinkler. The subsurface irrigation is another water system wherein water is applied straightforwardly inside the soil (Orang *et al*., 2008). The deficit irrigation method was an efficient strategy for Mediterranean environment land considering drought tolerant crop (Galindo *et al*., 2018; Hargreaves and Samani, 1984). The surface irrigation strategy is most widely utilized method and this methodology is generally popular and prudent but the low water system proficiency is the key issue (Raghuwanshi *et al*., 2010). The sprinkler water system structure includes pipe network water streams with power through spouts and it mimics precipitation with of overhead splashing (Valipour, 2015). In trickle water system, water is provided through fixed model line organization and gradually discharged to plants (Tindula *et al*., 2013). The advancement of first generation water system innovation was begun with multi-customer electronic hydrants for usage at regulation organization. The second era water system innovation was variable recurrence siphons. The micro-irrigation system strategy was the third era in irrigation innovation wherein WP was expanded however hardly introduced because of high initial speculation. The sub surface trickle water system was the fourth era in irrigation innovation designed to address the difficulties of surface drip water system, wherein producer obstructing issue is killed. The fifth era in water system innovation was deficiency water system developed for ideal water application considering crop development stage without influencing the yield (Levidow *et al*., 2014; kang *et al*., 2017). Artificial intelligence (AI) based water system frameworks are likely ways to deal with affordable and effective models for agricultural water management (Torres-Rua *et al*., 2012; Niu *et al*., 2017; Chlingaryan *et al*., 2018; Behmann *et al*., 2015; Griffiths *et al*., 2011; Gutierrez *et al*., 2018; Haider *et al*., 2008; Kamilaris and Prenafeta-Bouldu, 2018).

2. Land Suitability for Different Irrigation Methods

The land suitability for surface and micro-irrigation system was dissected utilizing parametric assessment strategy to decide the possible technique. The dirt properties were utilized to decide the reasonable water system technique in Fakkeh area of West Iran. The investigation displayed that trickle water system technique improved land sufficiency over sprinkler and surface strategy. The dirt surface was restricting variable for surface and sprinkler strategy, calcium carbonate was central question for drip irrigation system (Landi *et al*., 2008). The dirt properties were utilized to decide the appropriate water system techniques in Abbas plain territory of West Iran. The dirt properties were utilized to decide the appropriate water system strategy in Dosalegh locale of Iran. The investigation displayed that drip water system technique improved land sufficiency over sprinkler and surface strategy. The dirt surface, saltiness and incline were restricting components for surface and sprinkler strategy, calcium carbonate, soil surface and saltiness were key restricting variable for drip water system (Albaji *et al*., 2010). The dirt properties were utilized to decide the appropriate water system strategies in Gotvand plain zone of Iran. The investigation showed that sprinkler water system strategy improved land sufficiency over trickle and surface technique. The calcium carbonate and seepage were restricting variables for all water system strategies (Albaji *et al*., 2014). The dirt properties were utilized to decide the appropriate water system strategy in Rasht area of Iran. The investigation showed that trickle water system strategy improved land ampleness over sprinkler and surface technique. The dirt surface and seepage were key restricting variables for all the water system techniques (Seyedmohammadi *et al*., 2016). The audit of soil properties and land appropriateness model shows that micro-irrigation system surpasses surface water system over expanding irrigation land inside the accessible water resources.

3. Irrigation Methods

The irrigation method adoption depends on soil and land characteristics, WP and Economic water productivity (EWP). In the following section the basin, tube sprinkler, pillow and drip irrigation strategies were compared over investment, electricity cost, water usage efficiency and crop yield. The furrow and deficit drip strategies were compared on water savings and yield. The surface drip and sub surface drip were compared over emitter clogging, water consumption and yield. The drip and sprinkler methods were analyzed over delivery efficiency.

3.1. Comparison of basin, pillow, drip, and tube sprinkler irrigation

To address water scarcity, a field study was carried out at North China Plain, the three micro-irrigation methods improved WP but EWP of basin irrigation method was higher compared to micro irrigation methods. The comparisons of drip, basin, pillow and tube sprinkler irrigation methods are represented in Table 1 and Figure 1.

Table 1: Comparison of basin, tube sprinkler pillow and drip irrigation methods

References	Irrigation method	Investment cost (Yuan/ha)	Electricity cost (Yuan/ha)	Irrigation depth applied (mm)	WP (kg/m^3)	Yield (kg/ha)	Crop species
Fang *et al*., (2018)	Basin	700	0.22	90	1.57	6217.5	Winter wheat
	Drip	4125	0.33	90	1.91	6937.8	
	Pillow	3225	0.35	90	1.73	6898.3	
	Tube Sprinkler	4443	0.26	90	1.63	6614.5	

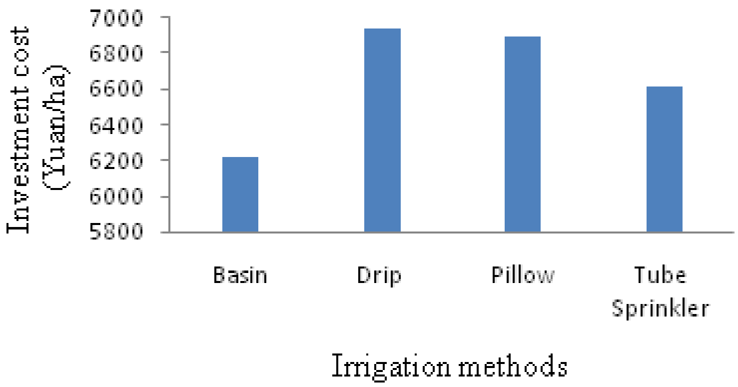

Figure 1: Comparison of different irrigation over investment cost

3.2. Comparison of furrow and drip irrigation

In a semiarid region a field study was conducted on drip and furrow irrigation for sugar beet to analyze WP. The drip tape irrigation method surpasses furrow method on sugar beet with higher WP. The details of water savings and yield are represented in Table 2 and Figure 2.

Table 2: Comparison of furrow and drip irrigation on WP

References	Irrigation method	Water savings compare to furrow irrigation		Average yield (t/ha)	Crop species
		with monitoring	without monitoring		
Ghamarnia *et al.*, (2011)	Drip (100% ET)	28.8%	38.4%	15.55	Sugar beets
	Drip (75% ET)	46.6%	53.8%	14.62	
	Drip (50% ET)	64.5%	69.2%	11.78	
	Drip (25% ET)	82.2%	84.6%	9.36	

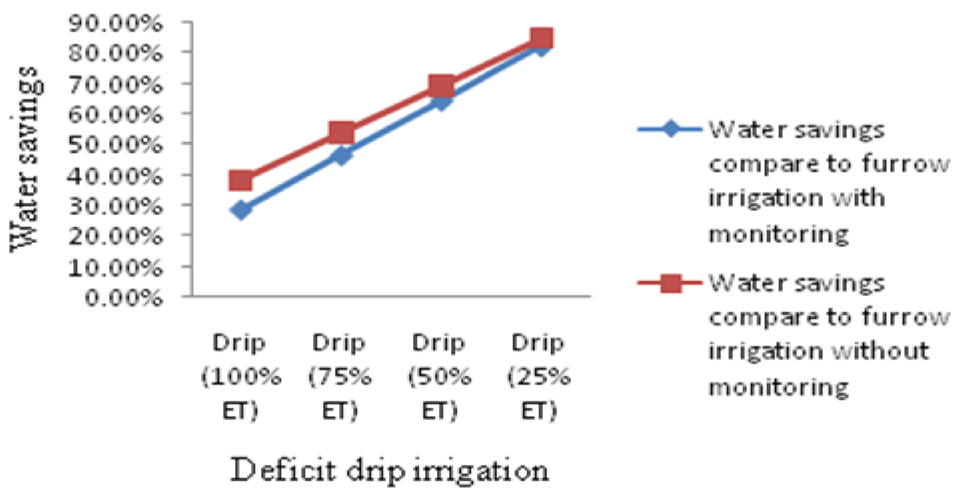

Figure 2: Comparison of furrow and drip irrigation over WP

3.3. Comparison of surface drip (DI) and subsurface drip irrigation (SDI)

Irrigation efficiency is an important issue in semiarid region due to water scarcity. Detecting leakages and repairing them is difficult task in surface drip irrigation though it is very efficient method. To overcome the drawbacks mentioned above an alternative subsurface irrigation system was introduced in southern Spain. The subsurface drip irrigation WP was high comparing to traditional drip irrigation method and easy to install. Comparison of DI and SDI based on WP are outlined in Table 3.

Table 3: Comparison of DI and SDI based on water WP and yield

References	Irrigation method	WP (kg/m^3)	Average yield (kg/tree)	Emitter Clogging issue	Crop species
Martinez and Reca, (2014)	DI	0.22	17.15	More exposure to emitter clogging and difficulty to detect clogged emitters and leakages.	Organic olive orchard
	SDI	0.24	19.24	Reduced exposure to emitter clogging and also easy to detect and replace clogged emitters.	

3.4. Analysis of sprinkler and drip irrigation

The drip and sprinkler irrigation strategies were compared on delivery efficiency (DE), maintenance cost and economy. The WP in drip irrigation system was lower than sprinkler irrigation system, in most of the plots water supply was higher than the actual requirement of water by crops. According to water users associations the sprinkler irrigation system has higher EWP than drip irrigation system (Corcoles *et al*., 2011). The comparison of sprinkler and drip irrigation performance are summarized in Table 4.

Table 4: Comparison of drip and sprinkler irrigation on economy and efficiency

References	Irrigation method	DE (%)	MOMId (€/m^3)	Energy Cost	OIa (€/ha)	Crop species
Corcoles *et al*., (2011)	Sprinkler	92.7	0.05	45% of MOM	4,408.16	Maize, Barley, Alfalfa, Onion, Carrot, Vineyard
	Drip	80	0.13	20% of MOM	2,388.16	Vineyards, Olive trees, Almond trees

MOMId = Management, Operation and Maintenance cost per unit irrigation delivery, OIa = Economic output per unit irrigation area.

4. Soft Computing (SC) Techniques for Irrigation System

SC is a space of software engineering that emulates marvel of human mind (Gocic *et al*., 2015). The perspectives, for example, cognizance and perception are key highlights of SC strategies. The SC techniques abuse obstruction for vulnerability and imprecision and also guarantee similarity and offers prudent arrangements. (Keskin and Terzi, 2006). To assemble smart and reasonable machines SC strategies have been utilized in numerous applications including ET_0. The ET_0 is a significant measurement to comprehend the harvest water prerequisites to acquire good yield (Temesgen *et al*., 2005). The ET_0 is crucial parameter for estimation of irrigation water requirements (Allen *et al*., 1991).

4.1. Neural networks (NN) for irrigation system

NN is an anatomical organization utilized for modelling non-linear systems using artificial intelligence methods. The NN data preparing structure is made like human neural organization and it comprises of three fundamental components, for example, input, concealed layers and yield. Shrouded layers among info and yield have number of neurons, hubs or cells. Information signal from the info layer arrives at the following connection by following all conceivable association ways and at each connection signal goes through change. NN comprises of many handling components arranged by connections and loads since its gigantic equal framework (Keskin and Terzi, 2006). The NN can gauge the cycle conduct even with halfway data. To gauge ET_0 neural organization models were utilized with various methodologies. In this section different neural organization strategies utilized for forecast of ET_0 are described.

The Artificial NN (ANN) and NN integrated with auto regressive external input (NNARX) models performance were analyzed in hot and dry environment (Piri *et al*., 2009). Multiple regression (MLR) and NN model efficiency was analyzed considering humidity and temperature data (Laaboudi *et al*., 2012). Adaptive neuro-fuzzy inference system (ANFIS) model was analyzed for climate data of Kerman and Isfahan station (Karimaldini *et al*., 2011). The ANN and Evolutionary NN (ENN) models were analyzed for forecast of ET_0. The feed forward back propagation NN (FFBP-NN) and second order NN (SONN) models were investigated for forecast of ET_0 (Adamala *et al*., 2013). Cuckoo search algorithm (CSA) was integrated with NN (ANN+CSA) and ANFIS was integrated with CSA (ANFIS+CSA) for forecast of ET_0 over twelve stations climate data of Serbia (Shamshirband *et al*., 2015). Back propagation neural networks (BPNN) was applied to forecast ET_0 with the help of hybrid particle based back propagation (PF-BP), Imperialist competition algorithm (ICA-BP) was used for forecast of ET_0 over Tabriz weather station data (Nazari and Shamshirband, 2018). Regression technique was applied for ET_0 prediction (Khoshravesh *et al*., 2017). The survey reveals that PF-BP and ENN model surpasses the different NN methods for forecast of ET_0.

4.2. Support vector machines (SVM) for irrigation system

SVM is a measurable learning hypothesis created by Vapnik. The informational collections of non-linearly distinct can be grouped by SVM utilizing kernels for plotting the information into high-dimensional component space. Support vector regression (SVR) is a way to deal with decide relapse through SVM. The fitting choice of bits and its boundaries portrays the performance of SVR model. Radial basis function (RBF) is the kernel function for SVM due to its favourable performance (Deo and Samui, 2017). Least square support vector machine (LSSVM) approach was applied to forecast ET_0 considering weather data from Shihez station of China and the prediction of LSSVM method was compared with ANN (Chen, 2011). The SVR approach was applied for forecast of ET_0 using regression procedures with SVM. The SVR model outperformed the other variants of SVM (Kisi and Cimen, 2009).

4.3. Genetic programming (GP) for irrigation system

The GP model discovers solution for issues utilizing traverse and change rules. Genetic calculation upholds equal inquiry dependent on Darwin development hypothesis. GP has self boundary choice potential to draw the features for improving the model without client impedance and it describes the program linearly. Genetic algorithm and back propagation (GABP) NN approach was applied to estimate ET_0 considering weather data of Tabriz station, Iran (Nazari and Shamshirband, 2018). A linear GP (LGP) was applied to forecast plant water requirement (Kisi and Guven, 2010). Gene expression programming (GEP) approach was applied to forecast plant water requirement using Egypt weather data (Mattar and Alazba, 2018). The LGP surpasses other GP variants for forecast of ET_0.

5. Intelligent Irrigation Systems

Approximately 60% of the flooded land must be smoothed out by adopting innovative irrigation methods to satisfy future global food demand and to extend WP (Alexandratos and Bruinsma, 2012; Playan *et al*., 2013). The SC strategies, agent technology, wireless Sensor Networks (WSN), Fuzzy decision support system (FDSS), Internet of Things (IoT) and have great potential to extend water savings in irrigation management. The review of innovative irrigation system exhibits the key features which help to improve the performance of irrigation system. The Fuzzy decision support system (FDSS) for irrigation was planned to address the particular issues of online water system model called IRRINET (Giusti and Marsili-Libelli, 2015). Agent based irrigation was planned considering soil properties, crop thirst affectability, development stage and net return estimation of harvest yield. The day by day water revive model was planned thinking about precipitation, ET_0, and introductory profundity of field water. The specialist model increases WP without yield reduction using regulated deficit irrigation. The depth of water required for daily recharge to maintain soil water balance was decided using volume of soil moisture depleted. The experiment was conducted for multi-crop farm land using priority based irrigation scheduling, which exhibits increased water productivity (Anthony and Birendra, 2018). To optimize water for agricultural crops automated irrigation system was developed. An intelligent irrigation system was designed using WSN, which comprises of temperature and dampness sensors inserted in the root zone of the yields, detected and handled information moved to a web machine. Based on temperature and soil moisture data for real time monitoring and programming of irrigation graphical user interface software was implemented (Gutierrez *et al*., 2014). The drip irrigation scheduling was implemented using java application software tool called IRRIX. The water balance model was employed for forecast of plant water requirement and recharge strategy was applied to balance the soil water, based on the feedback data of soil and plant sensor. Experiments were conducted for automated full and deficit irrigation with conventional method. Automated irrigation surpasses the conventional method through increase in WP and economy (Casadesus *et al*., 2012). Multi-intelligent control system (MICS) was used with the help of IoT for irrigation management. MICS provides reliable and satisfactory solution and also increases WP and EWP over conventional irrigation system (Hadipour *et al*., 2020). A smart irrigation system was proposed using IoT and neural networks approach. Crop water requirement data set was used to train the neural networks algorithm to get the accurate results. Intelligent irrigation was compared with normal drip and conventional irrigation methods, where in intelligent irrigation model surpasses the conventional methods through increased water productivity (Nawandar and Satpute, 2019). Automated drip irrigation was proposed using smart phone and microcontroller for paddy crop. It was compared with flood and normal drip irrigation. The smart phone captures the soil image, estimates the moisture and passes the data onto the microcontroller using GSM module. Automated drip out performs the normal drip and flood irrigation system (Barkunan *et al*., 2019).

5.1. Irrigation scheduling based on crop water stress

Intelligent root zone water quality model based irrigation was used to predict crop water pressure progressively. The depth of water needed for day by day revive to deal with soil water balance was set considering the depth of soil dampness drained. The yield water pressure based water system was adjusted with field water system utilizing drip and sprinkler technique for corn and soybean crops individually. The model expands the water system proficiency in low precipitation territory and it burns-through somewhat more water in moist territories with expanded harvest yield (Gu *et al*., 2017). The software model anticipated irrigation was calibrated with field drip irrigation, which is highlighted in Table 5.

Table 5: Comparison of software model based irrigation over field drip irrigation

References	Software model based irrigation	Water savings when calibrated with field drip irrigation for 3 years			Crop	Crop yield
		2008	2009	2010		
Gu *et al*., (2017)	Simulated for full water supply	30.5%	17.3%	7.1%	Corn	Negligible decrease between 0.03-3.81%
	Simulated for 60-90% of full water supply	35%	30%	16%		

The crucial input parameters are identified in the survey considering various irrigation systems and which can be used as features for machine learning based irrigation system. Comparison of machine learning, IoT, cloud and agent based irrigation systems over water savings are outlined in Table 6. The vital input features required for efficient irrigation systems are outlined in Table 7.

Table 6: Comparison of various software based irrigation systems on water savings

References	Technology	Water savings	Irrigation method	Crop species	Additional benefits	Experiment duration
Anthony and Birendra, (2018)	Agent technology	22.11% Without affecting the crop production.	Not mentioned	Pastures Maize Tomato Potato	High profit with priority-based water allocation	Not mentioned
Gutierrez *et al.*, (2014)	Wireless sensor networks	60%	Drip	Sage Thyme Origanum Basil	Energy autonomy And Low cost	18 Months
Giusti and Marsili-Libelli, (2015)	Fuzzy logic	13.55 % compare to irrinet model	Not mentioned	Corn Kiwi Potato Vegetable and Fruit crops	Robust and Consistent	2006-08
Gu *et al.*, (2017)	RZWQM2	35%	Drip, Sprinkler	Corn Soybean	Crop production improvement of 291 kg/ hectare	2008-10
Niu *et al.*, (2017)	Machine learning	Not mentioned	Not mentioned	Reeds Typha Orientalis Paddy	High Accuracy	Not mentioned
Severino *et al.*, (2018)	Internet of things (IoT)	Not mentioned	Drip	Not Mentioned	Usage of recycled water	Not mentioned
Zhou and Li, (2017)	Cloud services	Not mentioned	Not mentioned	Not Mentioned	Great market prospect	Not mentioned

Table 7: Key features identified for efficient intelligent irrigation system

References	SM	HU	ST	IM	CS	CG	CD	ET	RF	DP	RO
Anthony and Birendra, (2018)	✔		✔		✔	✔	✔	✔	✔		
Gutierrez *et al*., (2014)	✔	✔		✔	✔						
Giusti and Marsili-Libelli, (2015)	✔	✔	✔	✔	✔	✔		✔	✔		
Gu *et al*., (2017)	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
Niu *et al*., (2017)	✔	✔			✔	✔		✔	✔		
Severino *et al*., (2018)	✔		✔	✔	✔	✔	✔	✔	✔		
Zhou and Li, (2017)	✔	✔			✔	✔		✔			

SM= Soil moisture, HU= Humidity, ST= Soil type, IM= Irrigation method, CS= Crop species, CG=Crop growth stage, CD= Crop drought sensitivity, RF= Rain fall, DP= Deep percolation, RO= Runoff.

6. Performance Indicators for Irrigation System

The performance indicators play a vital role in rating irrigation systems (Pereira *et al*., 2012). In this section the key terminologies used for analyzing irrigation system performance are outlined. The ET determines the plant water requirement but how efficiently the irrigation system satisfies the need is computed through application efficiency (A_e). The AE is defined as the ratio of average depth of irrigation water consumed by crops and average depth of irrigation water applied. The aim of irrigation system is every part of the field should receive same amount of water. The distribution uniformity is defined as the ratio of average points of smallest water depth accumulated and average depth of water stored in all points. The irrigation efficiency (I_e) is the ratio of beneficially used irrigation water and gross volume of irrigation water that leaves the boundary. The irrigation consumptive use coefficient (I_{cu}) is defined as the ratio of depth of irrigation water consumptively used and gross volume of irrigation water that leaves the boundary. The irrigation sagacity (I_s) is the ratio that covers water usage for societal purpose along with crops consumption and gross volume of irrigation water that leaves the boundary. The other performance indicators such as adequacy (A_q), equity of water distribution (E_q), dependability of water supply (D_p), net Returns (N_r), yield Response, deep percolation ratio (D_r), tail water ratio (T_r), yearly relative water supply (Y_{rw}), yearly relative irrigation supply (Y_{ri}), Transmission loss (T_l), Outcome per planted area (O_{pa}), outcome per unit irrigated area (O_{ui}), outcome per unit irrigation applied (O_{ia}), outcome per unit irrigation depth consumed (O_{ic}), relative water supply (R_w), relative irrigation supply (R_i), irrigation water delivery capability (I_{dc}), dependability of duration (D_d), annual income (A_i), annual profit (A_p), net irrigation requirement (N_{ir}), net regulated deficit irrigation (N_{rdi}), seasonal irrigation performance index (S_{ipi}) are outlined in the following section. The survey of irrigation performance indicator model exhibited that, the water productivity and economic water productivity models are the effective measures to understand water savings and economy (Pereira *et al*., 2012). The irrigation performance indicator model to measure application efficiency is outlined in Table 8. The Irrigation performance indicator model to measure distribution uniformity (low quarter) is outlined in Table 9. The Irrigation performance indicators considering crop transpiration, evaporation, yield and profit are outlined in Table 10 (Appendix).

Table 8: Application efficiency models used in irrigation system

References	Model	Variables considered
Burt *et al.*, (1997)	$A_e = \frac{A_t}{A_a} \times 100$	A_e: Application Efficiency A_t: Average depth of irrigation water providing to target A_a: Average depth of Irrigation water applied
Ghamarnia *et al.*, (2011)	$A_e = \frac{I_a + I_c}{I_s}$	A_e: Application Efficiency I_a: Irrigation depth accumulated upon root zone (m^3) I_c: Irrigation depth consumed on the root zone (m^3) I_s: Total Irrigation depth supplied (m^3)
Raghuwanshi *et al.*, (2010)	$A_e = \frac{I_a}{q_0 W T_e} \times 100$	A_e: Application Efficiency I_a: Depth of irrigation water accumulated upon root zone (m^3) q_0: Flow in rate per unit border extent (m3/ m/s) W: Border extent (m) T_e: End time (s)
Reca *et al.*, (2018)	$A_e = 1 + f\left(\frac{D_r}{D_g} - 1\right) - \frac{\left(C_v - \frac{v^2}{2}\right)}{\left(\sqrt{\frac{\pi}{2}}\right)}$	A_e: Application Efficiency f: Fragment of the command area unit that is adequately irrigated. D_r : Irrigation depth requirement D_g : Total irrigation depth C_v: Coefficient variation of irrigation depth applied v: Cumulative variable

Table 9: Distribution uniformity low quarter (DU_{lq}) models used in irrigation system

References	Model	Variables considered
Burt *et al.*, (1997)	$DU_{lq} = \frac{AD_{lq}}{AD_{ef}}$	AD_{lq} : Average depth of irrigation water accrued in low quarter field AD_{ef} : Average depth of irrigation water accrued in entire field elements
Raghuwanshi *et al.*, (2010)	$DU_{lq} = \frac{\overline{AP_{lq}}}{\overline{AP}}$	$\overline{AP_{lq}}$: Average percolated depth for low field quarter (mm) $\overline{AP}$: Average percolated depth (mm)

7. Conclusion

Irrigation practices and software techniques applied for agricultural water management was reviewed to determine the effective method considering water productivity and economy. This paper reveals that, software techniques should be integrated with traditional irrigation methods to offer economical and efficient irrigation system. The empirical irrigation strategies were analyzed for water productivity and economy. This paper exhibits that, suppose if economy is the decision making factor, then surface irrigation is the best method over expensive micro-irrigation. Suppose if water savings is the key objective, then micro-irrigation technique is the best approach over surface irrigation system. The review of intelligent irrigation systems exhibits that, the software model based crop stress irrigation was the most effective technique with 30.5% water savings compared to field drip irrigation and this paper also reveals that software based irrigation system significantly improves water productivity. The soft computing model based forecast of reference evapotranspiration approach outperforms conventional models with minimal number of input features.

The survey opens-up future research on machine learning based surface irrigation system, which offers efficient and economical agricultural water management system. The machine learning based irrigation framework safeguards the advantage of low initial venture of conventional surface irrigation system with higher water productivity through the aid of artificial intelligence techniques. Real-time irrigation framework based on machine learning technique makes a significant improvement in water productivity.

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APPENDIX

Table 10: List of irrigation performance indicator models

References	Performance indicators	Model	Variables considered
Arunkumar and Ambujam, (2010)	T_l: Transmission loss	$T_l = \frac{R_i - R_o}{A_w \times R_l}$	R_i: Reach flow in rate (m^3/s) R_o: Reach flow out rate (m^3/s) R_l: Reach length (m) A_w: Avg. Wet area (m^2)
	O_{pa}: Outcome per planted area (Rs/ha)	$O_{pa} = \frac{CP_v}{P_a}$	CP_v: Crop production value as per local market price (Rs) P_a: Planted area (ha)
	O_{ui}: Outcome per unit irrigated area (Rs/ha)	$O_{ui} = \frac{CP_v}{A_{ui}}$	CP_v: Crop production value as per local market price (Rs) A_{ui}: Unit irrigated area (ha)
	O_{ia}: Outcome per unit irrigation depth applied (Rs/m3)	$O_{ia} = \frac{CP_v}{D_{ia}}$	CP_v: Crop production value as per local market price (Rs) D_{ia}: Depth of irrigation applied (m^3)
	O_{ic}: Outcome per unit depth of irrigation consumed (Rs/m3)	$O_{ic} = \frac{CP_v}{D_{ic}}$	CP_v: Crop production value as per local market price (Rs) D_{ic}: Unit depth of irrigation consumed (m^3)
	R_w: Relative water supply	$R_w = \frac{G_{id}}{ET_c}$	G_{id}: Gross irrigation depth supply (m^3) ET_c: Crop ET requirement (m^3)

Arunkumar and Ambujam, (2010)	R_i: Relative irrigation supply	$R_i = \frac{I_a}{I_r}$	I_a: Irrigation applied (m^3) I_r: Irrigation need
	I_{dc}: Irrigation water delivery capability	$I_{dc} = \frac{C_o}{R_{Peak}}$	C_o: Outflow capability of irrigation water at the system head R_{Peak}: Peak consumptive requirement
	D_d: Dependability of duration	$D_d = \frac{d_a}{d_p}$	d_a: Actual span of water supply (days) d_p: Planned span of water supply (days)
Broner and Lambert, (1989)	N_r: Net Returns	$N_r = (Y * C) - (I_a * I_e)$	Y: Yield (kg/ha) C: Cost ($/kg) I_a: Irrigation depth applied (cm) I_e: Irrigation expenditure ($/cm)
Burt *et al*., (1997)	I_e: Irrigation efficiency	$I_e = \frac{D_b}{D_a - D_s} \times 100\%$	D_b: Depth of irrigation water beneficially utilized D_a: Depth of applied irrigation water D_s: Depth of irrigation water storage
	I_{cu}: Irrigation consumptive use coefficient	$I_{cu} = \frac{D_c}{D_a - D_s} \times 100\ \%$	D_c: Depth of irrigation water consumptively utilized D_a: Depth of applied irrigation water D_s: Depth of irrigation water storage
	I_s: Irrigation sagacity	$I_s = \frac{D_{b/r}}{D_a - D_s} \times 100\ \%$	$D_{b/r}$: Depth of irrigation water beneficially / reasonably utilized D_a: Depth of applied irrigation water D_s: Depth of irrigation water storage
Corcoles *et al*., (2011)	Y_{rw}: Yearly relative water supply	$Y_{rw} = \frac{Y_{id} + E_p}{ET_c}$	Y_{id}: Yearly irrigation depth release (m^3) E_p: Effective precipitation (m^3) ET_c: Crop water consumption (m^3)

Corcoles *et al.*, (2011)	Y_{ri}: Yearly relative irrigation supply	$Y_{ri}= \frac{Y_{id}}{ET_c\text{- }E_p}$	Y_{id}: Yearly irrigation depth release (m^3) E_p: Effective precipitation (m^3) ET_c: Crop water consumption (m^3)
Hargreaves and Samani, (1984)	Yield response	$\left(1-\frac{Y_a}{Y_m}\right)= K_y\left(1-\frac{ET_a}{ET_m}\right)$	Y_a: Actual crop production Y_m: Maximum crop production K_y: Production response ET_a: Actual crop water consumption ET_m: Maximum crop water consumption
Memon *et al.*, (1986)	A_i: Annual income	$A_i = R_y * P_y * P_r$	R_y: Relative yield P_y: Potential yield P_r: Price
	A_p: Annual profit	$A_p = A_i - G_{ac}$	A_i: Annual income G_{ac}: Gross annual cost
Raghuwanshi *et al.*, (2010)	D_r: Deep percolation ratio	$D_r= \frac{D_{dp}}{q_o B_e T_e}$	D_{dp}: Depth of deep percolation (m^3) q_o: Flow in rate per unit border extent (m^3/ m/s) B_e: Border extent (m) T_e: End time (s)
	T_r: Tail water ratio	$T_r = 100 - D_r - A_e$	D_r: Deep percolation ratio A_e: Application efficiency
Rowshon *et al.*, (2014)	A_q: The adequacy of irrigation	$A_q= \frac{1}{t}\sum_1^i\left\{\sum_1^i\left[\frac{1}{i}\left(\frac{Q_d}{Q_r}\right)\right]\right\}$	t: Time periods for water supply i: Unit area belongs to a channel released by the system over time t. Q_d: Daily actual discharge Q_r: Irrigation need
	E_q: The equity of water distribution	$E_q=1-\frac{1}{t}\sum_1^i C_{vr}\left(\frac{Q_d}{Q_r}\right)$	C_{vr}: Spatial coefficient of variation
Rowshon *et al.*, (2014)	D_p:The dependability of the water supply	$D_p=1-\frac{1}{i}\sum_1^i C_{vt}\left(\frac{Q_d}{Q_r}\right)$ When $Q_d \leq Q_r$	C_{vt}: Temporal coefficient of variation

Stambouli *et al.*, (2011)	N_{ir}: Net irrigation requirement	$N_{ir} = (K_c * ET_0) - E_{rf}$	ET_0: Reference plant water consumption E_{rf}: Effective rain fall K_c: Plant Coefficient
	N_{rdi}: Net regulated deficit irrigation	$N_{rdi} = (K_c * K_{rc} * ET_0) - E_{rf}$	K_{rc}: Reduction coefficient
	S_{ipi}: Seasonal irrigation performance index	$S_{ipi}= \frac{N_{ir}}{I_{ad}}$	N_{ir}: Net irrigation requirement I_{ad}: Irrigation application depth
Pereira *et al.*, (2012)	WP: Water productivity (kg/ m3)	$WP = \frac{Y}{I_{ws}}$	Y: Yield (kg/ha) I_{ws}: Irrigation water supplied (m^3)
Cetin and Kara, (2019)	EWP: Economic water productivity ($/m3)	$EWP = \frac{N_r}{I_a}$	N_r: Net returns ($) I_a: Irrigation depth applied (m^3)