"Artificial Intelligence (AI) for Sustainable Water Resources Management (SWRM) in the GCC Countries"

Challenges of Artificial Intelligence in Managing Irrigation Water in the GCC Countries

Abdulrasoul Alomran

Arafat alkhasha

Soil Science Department, College of Food and Agriculture Sciences, King Saud University, Riyadh, Saudi Arabia.

rasoul@ksu.edu.sa

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INTRODUCTION

- Irrigation methods, water scarcity, and their management are critical, especially in agricultural lands of arid and semi-arid regions in the world.
- Agriculture accounts for nearly 80% of GCC's freshwater use and 70% of the global.
- Traditional irrigation methods are inefficient.
- Smart irrigation strategies that apply water at the right time and amount have been critical for good plant growth and hence crop productivity.

WHAT IS ARTIFICIAL INTELLIGENCE, OR AI?

When it comes to farming, artificial intelligence is a fancy name for ‘turning data into useful information to conserve irrigation water and better management’.

“AI can give us new information sooner for traditional farming decisions. But it can also give us information on new things we would once never have dreamed of,”

“But the most exciting part of bringing AI into farming is its power to make predictions. For example, we can make an accurate, evidence-based yield prediction even before we plant a crop.”

The use of meteorological, soil data and plants indicators for decision-making in irrigated agriculture has been a fully settled using imperical equations.

IMPORTANCE OF SMART IRRIGATION WITH AI

Enhances water-use efficiency.

Improves crop productivity and resilience.

Reduces energy and labor costs.

Prevents groundwater depletion and soil salinity.

Supports climate change adaptation.

MECHANISM OF AI-BASED SMART IRRIGATION

1. Data Collection: sensors, weather stations, satellites.

2. Data Processing: IoT + AI integration.

3. Prediction Models: machine learning for crop water needs.

4. Automated Control: precise irrigation scheduling.

5. Results: Increase the irrigation efficiency

GLOBAL EXPERIENCES OF AI IN IRRIGATION AND WATER MANAGEMENT

- **United States (California)**

- Faced with drought, farms adopted **AI + IoT systems** for real-time soil moisture monitoring.
- **IBM Watson Agriculture** developed predictive models using weather and satellite data.
- Some farms reported **25% water savings.** (Twarakavi et al.2021)
- **"AI-based irrigation scheduling can reduce water usage by up to 30% while increasing crop yields by 20% in Hawaii."**

. China

•Project in **Hebei Province** uses AI with drones and satellite imagery to monitor crop growth.

•Provides **field-specific irrigation recommendations** instead of uniform watering. (precision agriculture)

•Achieved **20% reduction in water use** and higher grain productivity

- The **Murray-Darling Basin** conducted an IoT and AI decision support system pilot project that cut water usage **by 35%** without affecting cotton production rates (Parr et al., 2022).

  - In India, the results of studies have shown that the use of artificial Intelligence tools is a viable alternative to increase crop production and efficiency in the use of natural resources, among which water is one of the most relevant (Udutalapally et al., 2020).

- The Tamil Nadu Agricultural University **in India built** a low-cost IoT-AI system for drip irrigation, and this technology enhanced rice production **by 20%** while attracting use from the small farmer community (Ahmad & Nabi, 2021).

AUSTRALIA

- **Outcomes and Impact**
- The adoption of AI-powered irrigation has provided measurable benefits:
- **Water Savings**: Farms using these systems have reported up to 25% savings in water usage, a crucial factor in drought-prone regions
- **Increased Yields**: Proper water management leads to healthier crops and increased yields, boosting farm profitability even for small-scale operations.
- **Sustainability**: By reducing water waste, small farms can also lower their environmental footprint, contributing to more sustainable farming practices.
- **Challenges**: Initial setup costs can be a barrier, though these are often offset by long-term savings in water and increased crop yields. Farmers may also need minimal training to understand the basic operation of AI-powered irrigation.
- **Lessons for Similar Businesses:** For small farms, starting with an AI-powered irrigation system provides a low-risk entry into the use of AI technology. This is an easy-to-adopt solution that requires minimal ongoing management, making it ideal for operations with limited technical expertise.

- Summarize the challenges as follows:
- 1. ***Data quality and availability***: Inaccurate or incomplete data can affect AI model performance.
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- 2. ***Sensor reliability***: Faulty sensors can provide incorrect data, impacting AI-driven decisions.
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- 3. ***Complexity of water systems***: Interactions between soil, climate, and crops can be difficult to model accurately.
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- 4. ***Scalability***: AI solutions may not be scalable to different farm sizes, crop types, or regions.
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- 5. ***Interpretability***: Understanding AI-driven decisions can be challenging for farmers and water managers.

- 6. ***Integration with existing systems***: AI solutions may require integration with existing infrastructure and systems.
- 7. ***Cost and accessibility***: Implementing AI solutions can be costly, and accessibility may be limited in rural areas.
- 8. ***Cybersecurity***: Connected systems can be vulnerable to cyber threats.
- 9. ***Regulatory frameworks***: Existing regulations may not support the use of AI in irrigation water management.
- 10. ***User adoption***: Farmers and water managers may need training and support to use AI-driven solutions effectively.

5 Types of Irrigation System

01
Surface Irrigation (a.k.a. Flood or Furrow Irrigation)

02
Drip or Micro Irrigation

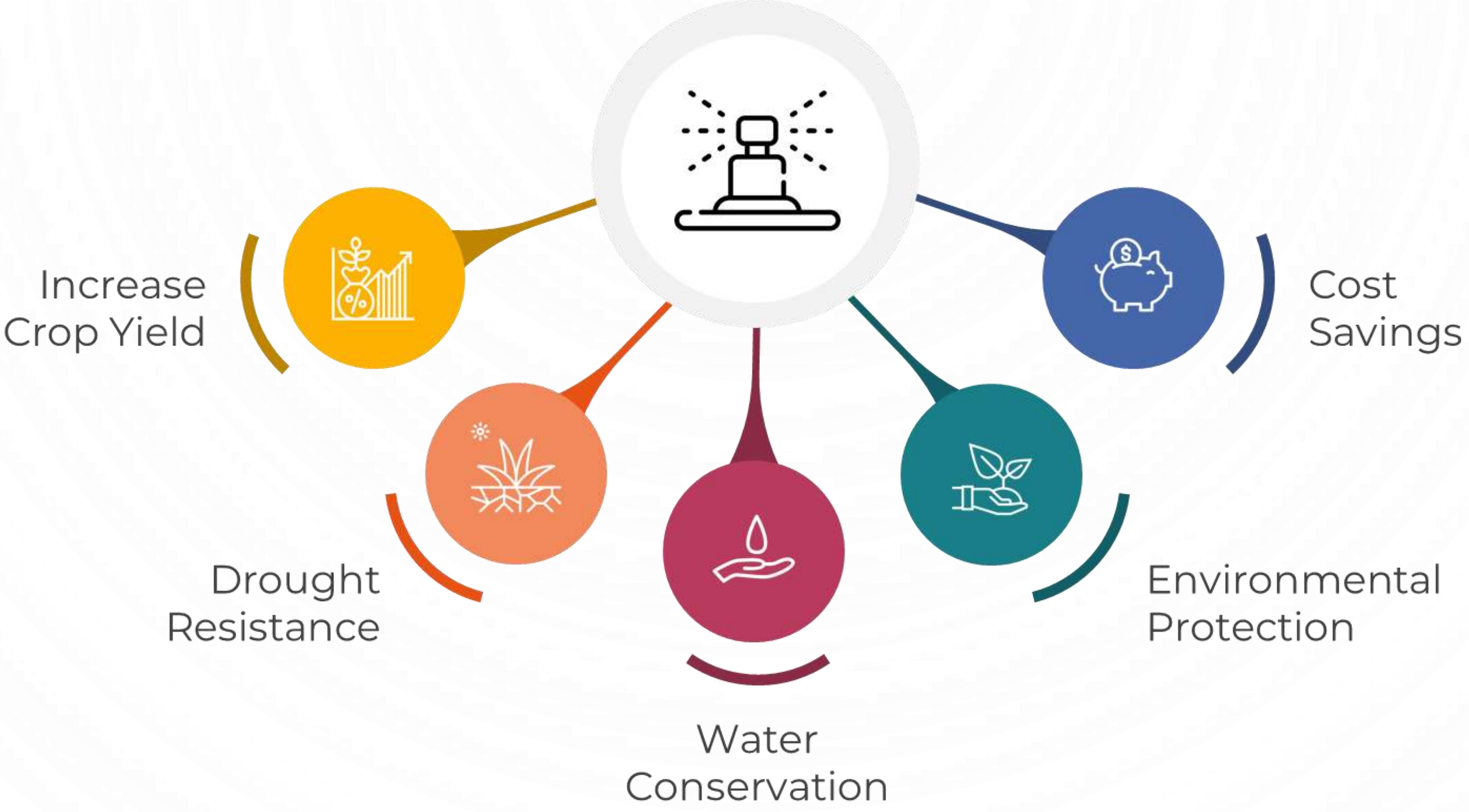
03
Sprinkler Irrigation

04
Center Pivot Irrigation

05
Sub Irrigation

Irrigation System

Irrigation System are Important for Several Reasons



Crop water requirements

TABLE 1 Summary of soil-based precision irrigation control approaches.

Author	Year	Sensing/Measurement			Application scope			Modeling/Control approach
		Soil	Plant	Atm	Field	Zone	Plant	
Adeyemi et al.	2018	x		x	x			MPC with NN-based prediction
Andugula et al.	2017	x				x		Gaussian process regression
Bazzi et al.	2019	x				x		Fuzzy C-means algorithm
de Benedetto et al.	2018	x			x			Kriging with external drift
Benzekri and Refoufi	2006	x		x	x			Anticipatory on/off control
Capraro et al.	2008	x				x		on/off control with dynamic thresholds
Chen et al.	2020					x		Genetic algorithm
Egea et al.	2017	x			x			on/off control
Gu et al.	2021	x		x	x			NN-based on/off control
Hedley and Yule	2009	x				x		Daily prediction of soil water status
Jimenez et al.	2020	x			x			LSTM neural network
Liu and Xu	2018	x					x	On/off control
Lou et al.	2016	x	x		x			On/off control
Nahar et al.	2019	x		x	x			MPC with closed loop scheduling
Roy	2014	x			x			MPC with stochastic receding horizon
Song et al.	2016	x		x	x			Deep belief network (DBN)
Termite et al.	2019	x		x	x	x		Feedforward NN; ANFIS
Tseng et al.	2018		x		x		x	Deep convolutional neural network
Wei et al.	2013	x			x			On/off control
Xiao et al.	2010	x			x			on/off control
Xiao et al.	2010	x			x	x		on/off control
Zhao et al.	2007	x			x			On/off, Time control and fuzzy hybrid control

TABLE 2 Summary of atmosphere-based precision irrigation control approaches.

Author	Year	Sensing/ Measurement			Application scope			Modeling/Control approach
		Soil	Plant	Atm	Field	Zone	Plant	
Barker et al.	2018			x		x	x	VRI with remote sensing-based water balance model
Bhatti et al.	2019			x				satellite and airborne imagery-based VRI
Dominguez-Nino et al.	2020	x		x		x		model-predictive control (IRRIX software)
Farooque et al.	2021			x				deep learning model-based ET prediction
Fourati et al.	2014	x		x	x	x		FAO56 ET model-based on/off control
Gobbo et al.	2019	x		x		x		VRI with dynamic zone delineation
Gordin et al.	2019	x		x	x	x		Hargreaves-Samani ET model-based on-off control
Incrocci et al.	2014	x		x		x	x	Soil moisture-based vs. ET-based automated drip irrigation
Linker et al.	2018			x	x			MPC with real-time multi-objective optimization
Lorite et al.	2015			x	x			weather forecast-based on/off irrigation control
Lozoya et al.	2016	x		x	x	x		model-predictive control with soil moisture measurement
Ma et al.	2017	x		x	x			weather forecast-derived ET-based deficit irrigation
Pelosi et al.	2019		x	x	x			calibrated Hargreaves-Samani for ET modeling
Robinson	2017			x	x	x		plant-specific Penman-Monteith model-based control
Roy	2014	x		x	x	x		stochastic receding horizon approach
Sidhu et al.	2020			x	x			Regression-based on/off scheduling
Tsakmakis et al.	2016	x		x	x	x		interoperable model coupling for irrigation scheduling (IMCIS)

Materials & Methods

Reference Evapotranspiration

FAO Pan methodologies (**ET$_{o\text{-pan}}$**)

$$ET_{o-pan} = E_{pan}(0.61 + 0.00341.RH_{mean} - 0.000162.u_2.RH_{mean} - 0.00000959.u_2.FET + 0.00327.u_2.ln(FET) - 0.00289.u_2.ln(86.4\,u_2) - 0.0106.ln(86.4\,u_2).ln(FET) + 0.00063.[ln(FET)]^2.ln(86.4\,u_2))$$

FAO Penman-Monteith approach (ET$_{o\text{-PM}}$)

$$ET_{o-PM} = \frac{0.408\,\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.23u_2)}$$

The radiation method (ET$_{o\text{-FR}}$)

$$ET_{o-FR} = \begin{cases}(0.288 + 0.0019 \cdot JD) \cdot R_o \cdot \tau, & JD \geq 220 \\ (1.339 + 0.00288 \cdot JD) \cdot R_o \cdot \tau, & JD < 220\end{cases}$$

devices and equipment used for the different measurements

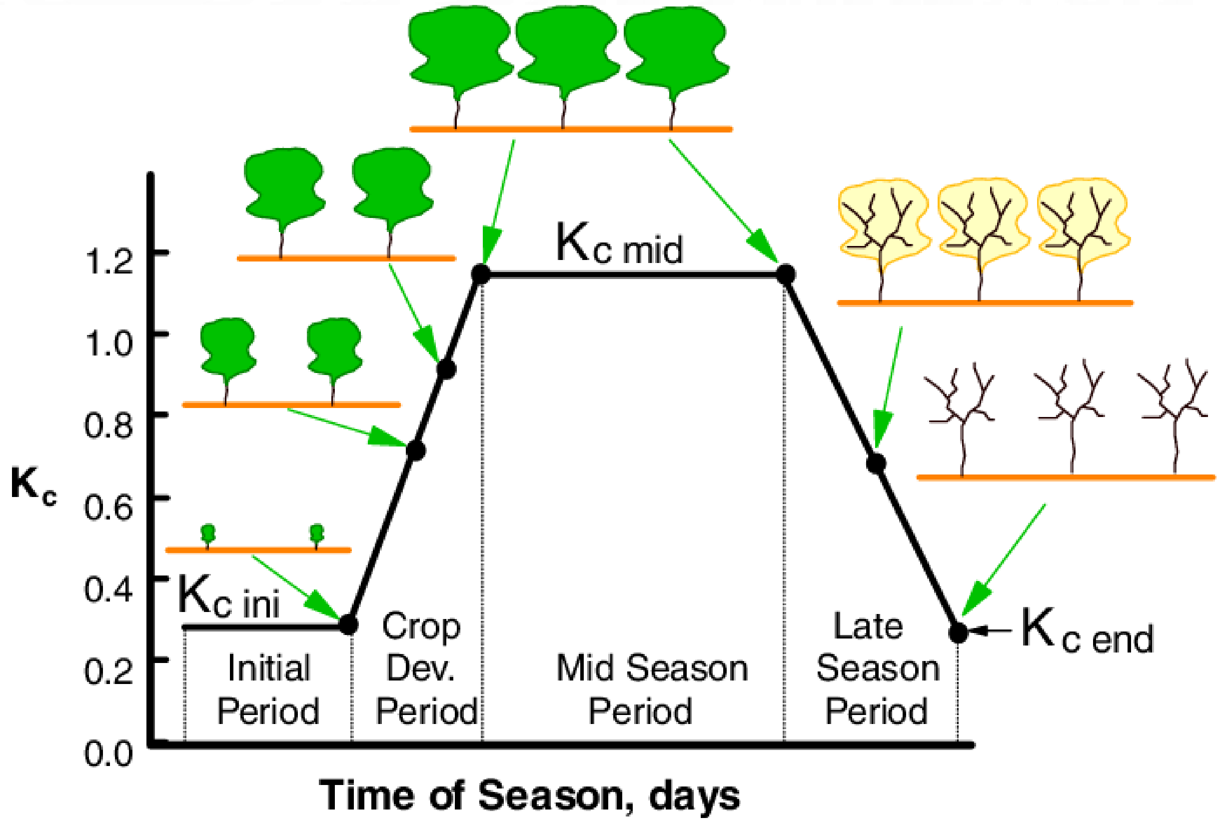
Actual Crop Coefficient

$$K_{c-act} = \frac{ET_c}{ET_o} = \frac{ET_{c-act(FI-FW)}}{ET_{o-pan}}$$

Water stress coefficient

$$K_s = \frac{ET_{c-act}}{ET_c} = \frac{ET_o K_c K_s}{ET_o K_c}$$

$$= \frac{ET_{c-act}}{ET_{c-act(FI-FW)}}$$



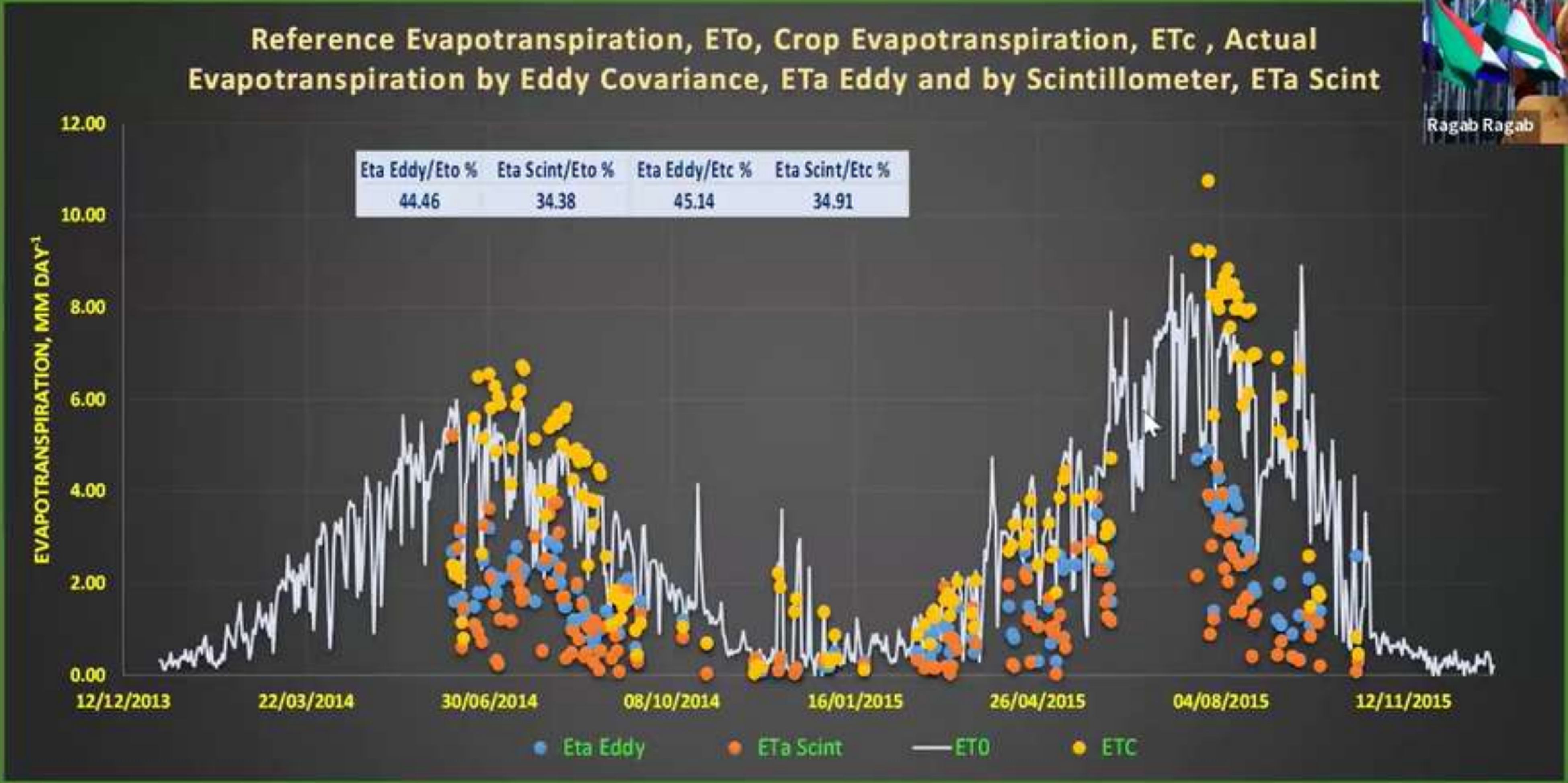

قياس كمية المطر
وحدة ارسال واستقبال البيانات
وحدة الطاقة الشمسية
قياس سرعة الرياح
قياس اتجاه الرياح
قياس الإشعاع
قياس الرطوبة ودرجة الحرارة

DATE PALM WATER REQUIREMENTS

- These estimates differ between 6200 and 55,000 m3 /ha. Alazba (2001) estimates water requirement to be between 15,000 and 55,000 m3 /ha, depending on the irrigation system or leaching requirement.
- Kassem (2007) monitored water requirements in the Qassim region, using the soil water balance method, and he determined the annual water use with drip irrigation as 16,400 m3 /ha, with a density of 100 trees/ha.
- Al-Amoud et al. (2012) estimated the actual water use in the range between 21,360 and 28,290 m3 /ha, for a density of 100 trees/ha.
- Ismail et al. (2014) calculated water requirement based on Penman–Monteith for ETo, Kc ranged from 0.8 and 1.0, and the evapotranspiration area (23 m2 / tree), to be 7300 m3 /ha, for a density of 100 trees/ha.
- In Kuwait, date palm water requirement was determined using drainage-type lysimeters through water balance and ranged between 23,392 and 27,251 m3 /ha. (Bhat et al., 2012)
- Alharbi et al. (2022). Estimated date water requirements to be 8200 m3/ha

ble 4 Comparison between Penman–Monteith calculations and actual amount of applied water in the different sites, and increase in w
tio (%) compared to Penman–Monteith method

te	Penman–Monteith method (m^3/ha/year)	Water balance method (m^3/ha/year)	Actual applied water (m^3/ha/year)		The increase in water ratio (%) compared to Penman–Monteith method	
			Field study	Farmer adjacent	Field study	Farmer adjac
edina	9495	–	11,305	13,717	16.0	30.8
ıbuk	7340	–	9463	12,277	22.4	40.2
akkah	7298	–	9692	12,220	24.7	40.3
l Jouf	8913	3515	11,252	13,340	20.8	33.2
iyadh	8614	–	10,007	12,050	13.9	28.5
assim	8568	3604	10,035	12,880	14.6	33.5
ail	7996	–	10,272	12,620	21.2	36.6
ıst Region	8510	–	10,082	12,610	15.6	32.5



Comparison between actual evapotranspiration measured by Eddy Covariance and Scintillometer, reference evapotranspiration estimated from Penman-Monteith equation and crop evapotranspiration calculated from ETo and the weighted mean of the crop coefficient Kc.

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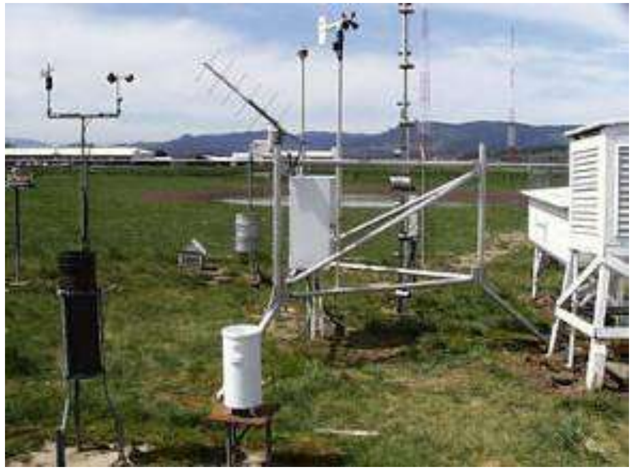
IRRIGATION SCHEDULING



- Important factors to keep in mind when developing a irrigation scheduling tool:
- The scheduling tool must consider information about the crop, soil, climate, irrigation system, water deliveries and management objectives.
- An irrigation scheduling tool needs only be accurate enough to determine how much water to apply and when.
- A good rule of thumb to follow when developing an irrigation scheduling tool is to keep it simple and easy to understand.
- A calibration of soil moisture sensor is must.

- Soil Sensor for measuring soil water content

MOST IMPORTANT FACTOR

Good soil to sensor contact

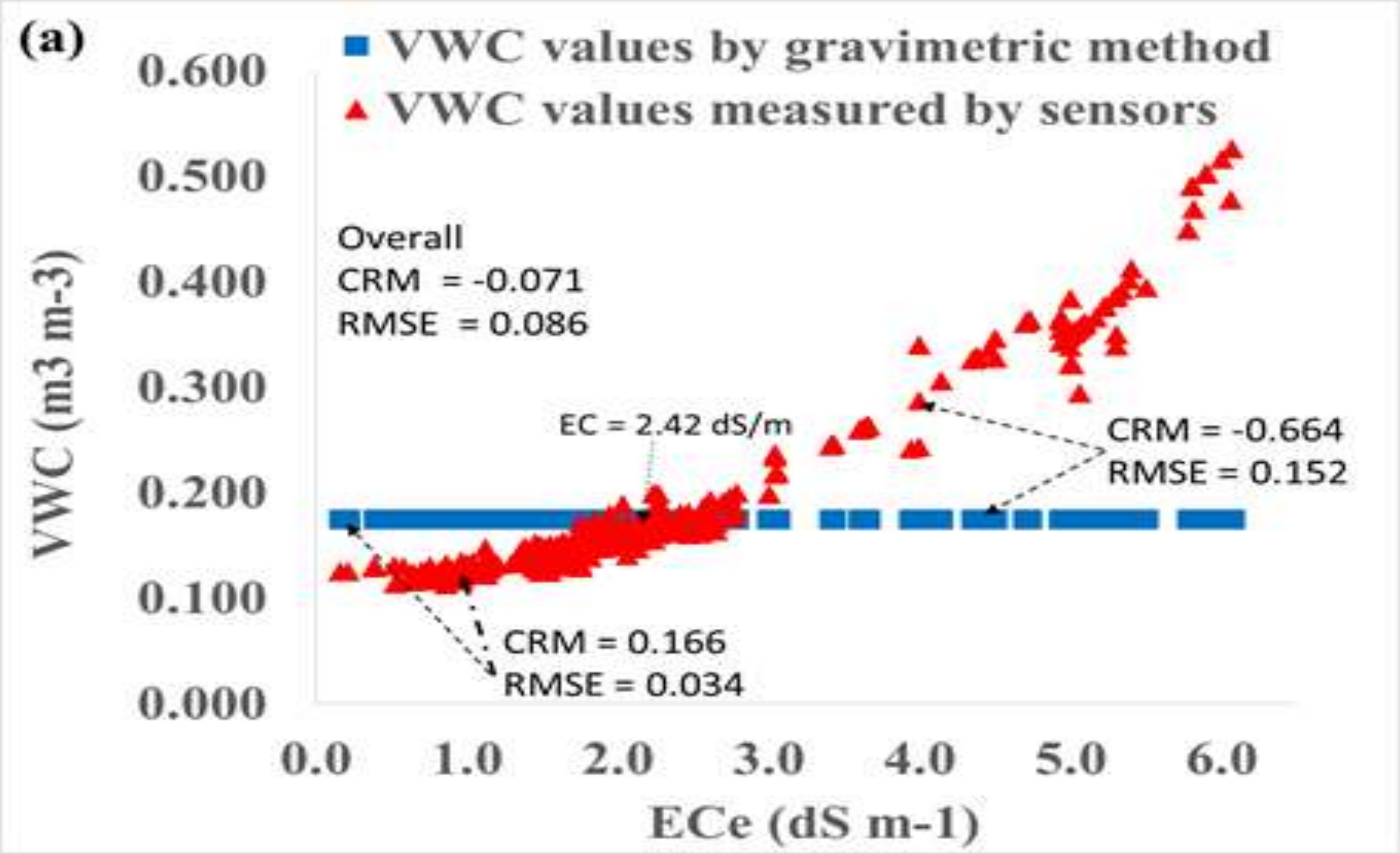
TEROS WATER CONTENT SENSORS

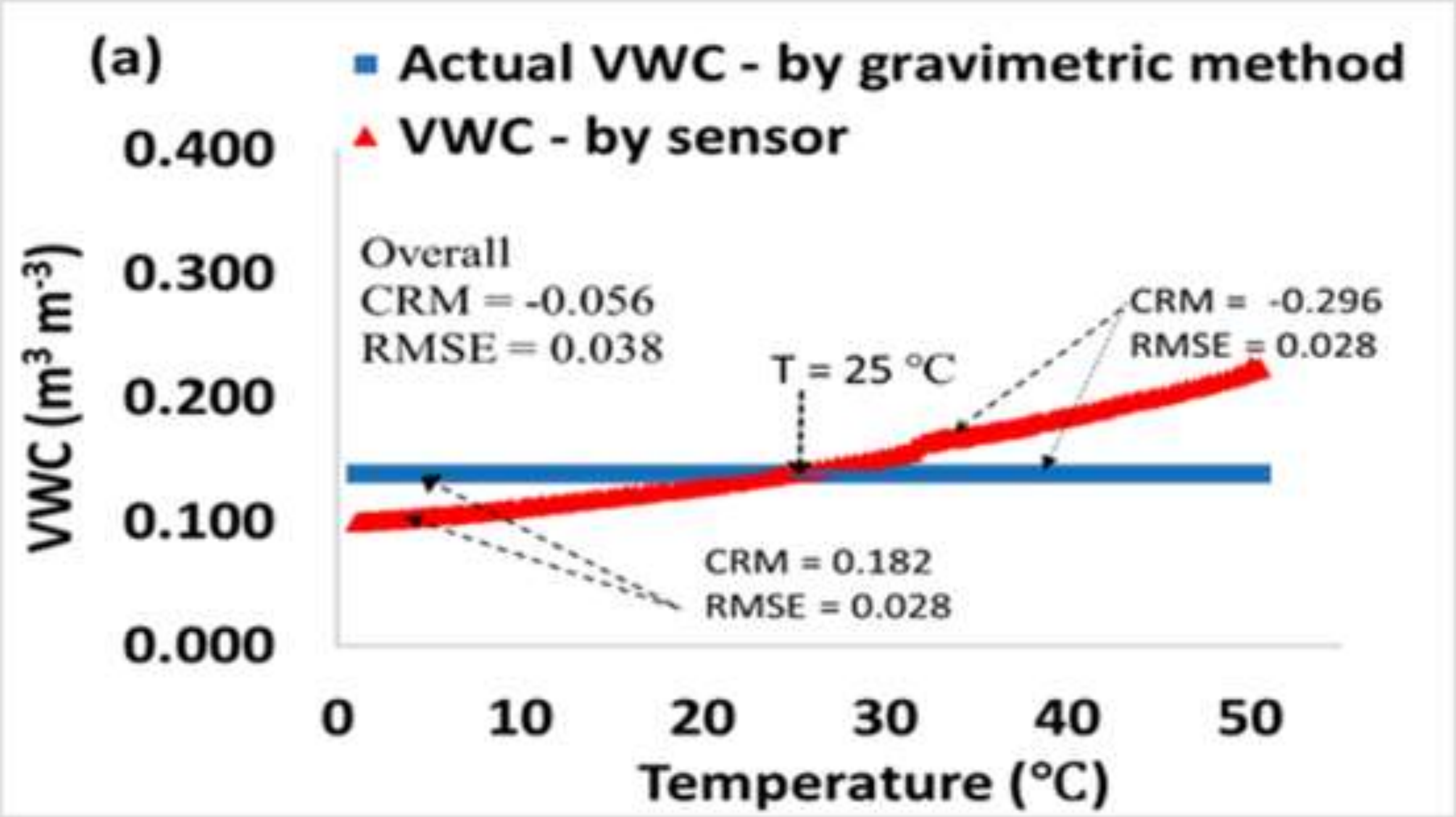
TEROS 12
- Water Content
- Temperature
- EC

TEROS 11
- Water Content
- Temperature

TEROS 10
- Water Content

TEROS 10
- Water Content & Temperature at 4 different depths


(a)
VWC values by gravimetric method
VWC values measured by sensors
Overall
CRM = -0.071
RMSE = 0.086
EC = 2.42 dS/m
CRM = -0.664
RMSE = 0.152
CRM = 0.166
RMSE = 0.034
0.600
0.500
0.400
0.300
0.200
0.100
0.000
0.0
1.0
2.0
3.0
4.0
5.0
6.0
VWC (m3 m-3)
ECe (dS m-1)



(a)
Actual VWC - by gravimetric method
VWC - by sensor
0.400
0.300
0.200
0.100
0.000
VWC (m3 m-3)
Overall
CRM = -0.056
RMSE = 0.038
T = 25 °C
CRM = -0.296
RMSE = 0.028
CRM = 0.182
RMSE = 0.028
0
10
20
30
40
50
Temperature (°C)

Irrigation and Drainage

Research Article

SENSOR EFFECTIVENESS FOR SOIL WATER CONTENT MEASUREMENTS UNDER NORMAL AND EXTREME CONDITIONS†

Ibrahim I. Louki, Abdulrasoul M. Al-Omran, Anwar A. Aly, Abdulaziz R. Al-Harbi

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https://doi.org/10.1002/ird.2377

† Efficacité des capteurs pour la mesure du contenu en eau du sol dans des conditions normales et extremes.

agronomy

MDPI

Article

Calibration of Soil Moisture Sensors (ECH_2O-5TE) in Hot and Saline Soils with New Empirical Equation

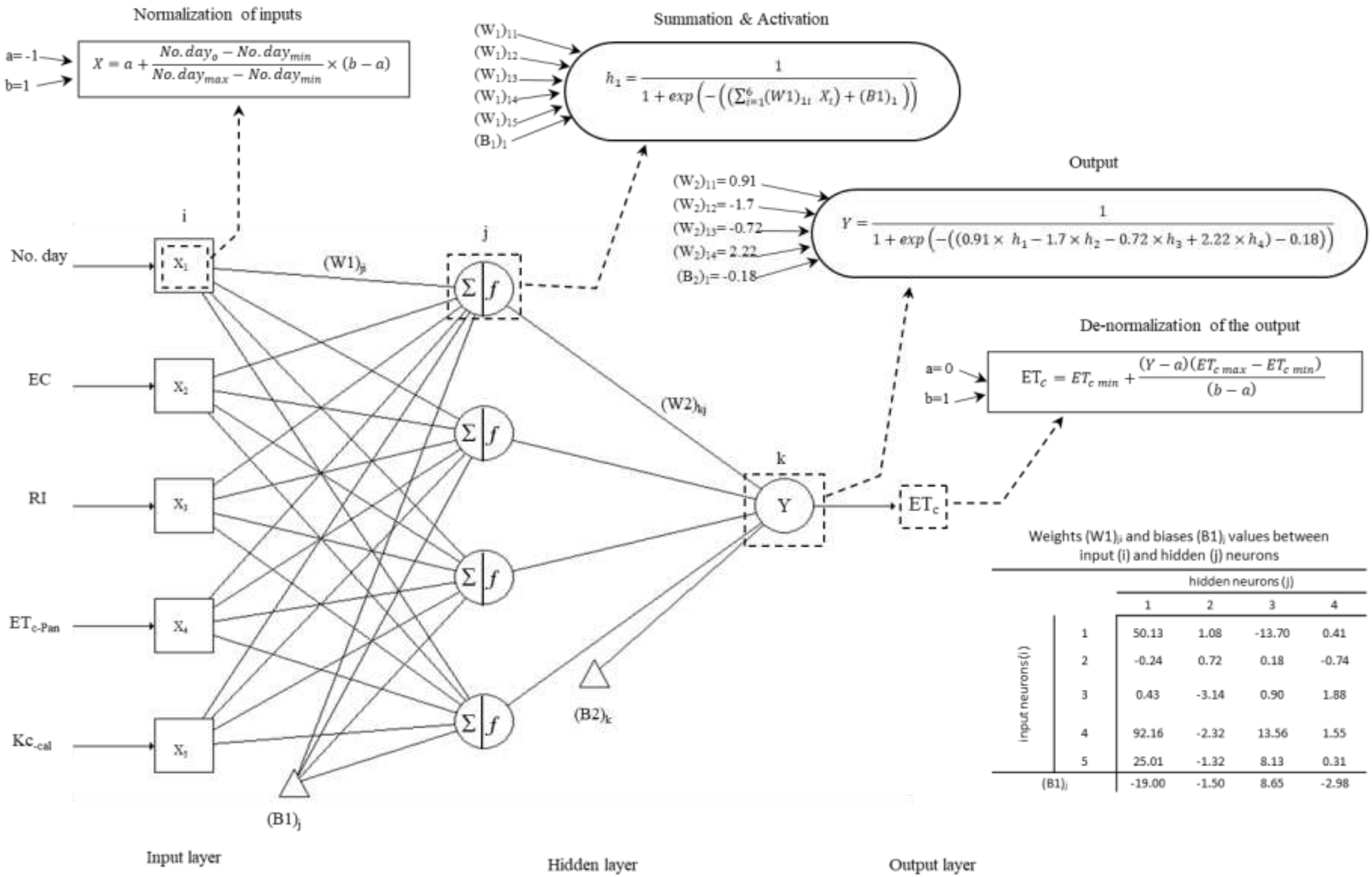
Ibrahim I. Louki [1,2] and Abdulrasoul M. Al-Omran [1,*]

[1] Soil Science Department, College of Food and Agriculture Science, King Saud University, Riyadh 11451, Saudi Arabia
[2] Al-Mohawis's agriculture Farm at Thadiq, Thadiq 11953, Saudi Arabia
* Correspondence: rasoul@ksu.edu.sa

Abstract: The use of soil moisture sensors is a practice applied to improve irrigation water management. ECH2O-5TE sensors are increasingly being used to estimate the volumetric water content (VWC). In view of the importance of the efficient use of these devices, six main factors affecting the accuracy of sensor measurements were studied: soil moisture levels, soil salinity, temperature,

Materials & Methods

Artificial neural network (ANN) models



Weights $(W1)_{ji}$ and biases $(B1)_j$ values between input (i) and hidden (j) neurons

input neurons (i)	hidden neurons (j) 1	2	3	4
1	50.13	1.08	-13.70	0.41
2	-0.24	0.72	0.18	-0.74
3	0.43	-3.14	0.90	1.88
4	92.16	-2.32	13.56	1.55
5	25.01	-1.32	8.13	0.31
$(B1)_j$	-19.00	-1.50	8.65	-2.98

Conclusions

- 1. Data quality and availability: Implement data validation processes to ensure accuracy.

- 2. Sensor calibration: Regularly calibrate sensors to prevent drift and ensure reliability.


THANK
YOU