

**UNDERSTANDING THE HYDROLOGICAL DYNAMICS OF
THE SOIL-PLANT INTERFACE UNDER DIFFERENT
IRRIGATION SCENARIOS IN ARID REGION - A SCALED
EXPERIMENT**

BY

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For God, the Nation, and the Almamater |

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LIST OF ABBREVIATIONS

ERT	: Electrical Resistivity Tomography
ETc	: Crop Evapotranspiration
ETo	: Reference Evapotranspiration
FAO	: Food and Agriculture Organization of the United Nations
GPR	: Ground Penetrating Radar
Kc	: Crop Coefficient
LAI	: Leaf Area Index
MAE	: Mean Absolute Error
RMSE	: Root Mean Square Error
RWU	: Root Water Uptake
SM	: Soil Moisture

ABSTRACT

Full Name : Arya Pradipta

Thesis Title : Understanding the Hydrological Dynamics of the Soil-Plant Interface under Different Irrigation Scenarios an Arid Region - a Scaled Experiment

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Plant roots are vital for water, nutrient, and carbon cycling in ecosystems, yet their study is hindered by inaccessibility. This research focuses on detecting and mapping fine plant roots in lemon trees using Ground Penetrating Radar (GPR) and Electrical Resistivity Tomography (ERT) under controlled conditions. GPR successfully identified root concentrations, particularly in the topsoil, and ERT captured root activity variations over seven months, underscoring its potential for precision agriculture. Additionally, the study used HYDRUS-1D and ERT to simulate root water uptake (RWU) in hyper-arid environments, revealing peak RWU in the morning and deeper RWU with rising temperatures. Moreover, the study assessed irrigation efficiency using the HYDRUS-1D model under different scenarios, finding that less frequent irrigation with larger doses minimized evaporation and maximized transpiration. By employing the relative transpiration rate (T_a/T_p) indicator, which is closely related to biomass production, this study found that irrigation frequency every 10 days (I_{10}) was the most optimum scenario as it generated the highest ratio of actual crop transpiration to potential transpiration. However, the optimum irrigation frequency is not constant, since it is affected by several variables, such as soil, climate, and crop type. Therefore, farmers and decision-makers should consider these variables in determining optimum irrigation frequency. These findings provide valuable insights for optimizing irrigation strategies and improving resource management in arid agroecosystems.

ملخص الرسالة

الاسم الكامل: آريا براديتا براشيتو

عنوان الرسالة: فهم الديناميكيات الهيدرولوجية في السطح البيئي بين التربة والنبات في ظل سيناريوهات ري مختلفة في منطقة قاحلة - تجربة مصغرة

التخصص: جيولوجيا

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الجذور الدقيقة للنبات تلعب دورًا حيويًا في دورة المياه والمغذيات والكربون في النظم البيئية، ومع ذلك، فإن دراستها تتعقد بسبب صعوبة الوصول إليها. يركز هذا البحث على اكتشاف وتخطيط توزيع الجذور الدقيقة للنبات في أشجار الليمون باستخدام في ظروف محكمة. نجح الرادار المخترق (ERT) والتصوير بالمقاومة الكهربائية (GPR) الرادار المخترق للأرض للأرض في تحديد تركيزات الجذور، خاصة في الطبقة العليا من التربة، بينما سجل التصوير بالمقاومة الكهربائية نشاط الجذور وتغيراته على مدى سبعة أشهر، مما يبرز إمكانياته في الزراعة الدقيقة. بالإضافة إلى ذلك، استخدم البحث نموذج والتصوير بالمقاومة الكهربائية لمحاكاة امتصاص الماء بواسطة الجذور في البيانات القاحلة للغاية، مما HYDRUS-1D أظهر ذروة الامتصاص في الصباح وعمقًا أكبر لامتصاص الماء مع ارتفاع درجات الحرارة. علاوة على ذلك، قام البحث بتقييم تحت سيناريوهات مختلفة، حيث وجد أن الري الأقل تكرارًا بجرات أكبر HYDRUS-1D كفاءة الري باستخدام نموذج الذي يرتبط بشكل وثيق بإنتاجية الكتلة (Ta/Tp) يقلل التبخر ويزيد من عملية النتج. باستخدام مؤشر معدل النتج النسبي كان السيناريو الأمثل حيث حقق أعلى نسبة من النتج الفعلي إلى (I_{10}) الحيوية، وجدت هذه الدراسة أن تردد الري كل 10 أيام النتج المحتمل. ومع ذلك، فإن التردد الأمثل للري ليس ثابتًا، حيث يتأثر بعدة عوامل مثل التربة والمناخ ونوع المحصول. لذلك، توفر هذه النتائج رؤى قيمة. يجب على المزارعين وصانعي القرار أخذ هذه العوامل في الاعتبار عند تحديد تردد الري الأمثل. لتحسين استراتيجيات الري وإدارة الموارد في النظم الزراعية القاحلة

CHAPTER 1

INTRODUCTION

1.1 Background

The earth critical zone can be defined as a near-surface layer of earth, ranging from the top of the vegetation canopy to the topmost groundwater zone, involving vegetation, soil, weathered bedrock, and water that are essential for supporting all types of life (Xu & Liu, 2017). The range of the earth critical zone varies significantly in space, depending on tectonic history, lithology, types of vegetation, and climate (Dawson et al., 2020). This zone is considered a very active and dynamic zone where many critical natural processes occur. This is the zone where the interaction between solar energy and gas fluxes with biota and rock mass can support the living ecosystem for human beings and all types of life. In this complex system, plants have a central role as an interface connecting the atmosphere and hydrosphere.

The soil-plant interface is a critical component of the earth's surface ecosystem as it influences the plant development, water cycle, critical zone processes and biodiversity. Even though it is difficult due to complexities, understanding the processes controlling mass and energy exchange in the soil-plant interface is beneficial, mainly to implement precision agriculture. Dynamic fluxes in this zone are governed by root architecture, water potential, water content and hydraulic conductivity. Identifying the root density or architecture is important since they have a critical function in acquiring water and nutrients from soil to the plant to grow (Feddes et al., 2001; Whalley et al., 2017). In the soil-plant-

atmosphere interface, root system provides the pathway for hydrological fluxes from soil environment to the atmosphere through the plant canopy (Feddes et al., 2001). Along with soil moisture (SM), root systems are the essential drivers governing natural processes and mechanisms in the root zone. In agricultural areas, SM variations are mainly driven by precipitation, evapotranspiration, and irrigation water supply, while root density is a function of soil, vegetation, and climate (Guswa, 2008).

A good understanding of the complex system in the soil-plant interface might allow for the improvement of water, soil, and crop management, which is beneficial for agricultural precision. However, our understanding of root systems is often constrained by the fact that they are hidden belowground biomass. Understanding the root characteristic in terms of spatial and temporal resolution is challenging to be achieved through traditional approaches such as excavation, soil pits or soil cores. These techniques are regarded as invasive approaches that are destructive, labor cost, and time-consuming despite allowing direct observation of the root system. Buried sensors and probes can accurately measure it, however, the cost and effort to conduct this experiment are prohibitive since the sensors are left in-situ (Whalley et al., 2017). Invasive sampling might disturb the natural state of the root system and affect the processes within the root zone, thus altering the experimental results (Ehosioke et al., 2020). In addition, those practices can be considered impractical and inefficient over large areas due to heterogeneity of subsurface properties. To overcome these issues, non-invasive or minimally invasive methods have been widely presented. One of them is near-surface geophysical techniques that can infer root characteristics at various scales with a minimally invasive impact.

Compared to traditional exploration geophysics that is mainly carried out to support oil, gas, and mineral industries, near-surface geophysics survey is often motivated not by profit concerns but to benefit society and address a wide range of scientific questions (Everett, 2011) (Everett, 2011). The use of near-surface geophysical techniques is commonly applied in geotechnical engineering (Chambers et al., 2014; Cueto et al., 2018), groundwater (Dildar et al., 2023; Jellalia et al., 2015; Sharafeldin et al., 2019), environmental assessments (Kirkou et al., 2015; Power et al., 2014), and archaeology (Basile et al., 2000; Francese et al., 2009; Shaaban et al., 2009) (Basile et al., 2000; Francese et al., 2009; Shaaban et al., 2009). Over the past decade, numerous attempts have been made to extend the use of near-surface geophysics for critical zone studies and agricultural applications (Garré et al., 2021; Jayawickreme et al., 2014) (Garré et al., 2021; Jayawickreme et al., 2014). These applications utilize different geophysical methods (e.g., electrical resistivity, electromagnetic, induced polarization, and seismic velocity) that exploit differences in the physical properties of earth materials within the subsurface. In this context, electrical resistivity tomography (ERT) and Ground Penetrating Radar (GPR) are considered the most promising techniques for accurate characterization of the near-surface.

The combination of geophysical techniques is commonly applied since the ambiguity of data interpretation from one particular method could be solved based on results from another technique. Therefore, the joint use of ERT and GPR is believed to provide complementary information about the root activity and biomass information. Moreover, in extreme hyper-arid environments (air temperatures and very high sand concentrations in soils) the use of geophysical techniques could give us accurate information on soil moisture

dynamics versus depth, overcoming the use of soil moisture sensors, which in sandy soils are extremely difficult to operate properly. Besides geophysical acquisitions, numerical models can help study complex processes in the soil-plant-atmosphere system. One of the numerical models that have often been used to simulate the movement of water in variably saturated media is HYDRUS-1D due to its simplicity compared to heavily parameterized physically based models (Er-Raki et al., 2021; Šimůnek, Genuchten, et al., 2016a). In agricultural applications, HYDRUS-1D has been widely used to simulate the root water uptake (RWU) under different crop, soil, and environmental condition and provide satisfactory results (Jha et al., 2017; X. Wang et al., 2021; Zheng et al., 2018). The parameters of direct field measurements required in HYDRUS 1D, such as soil water content and root geometry, are typically collected through the classical method, which is destructive and provides limited spatial coverage. This information can be derived by the applied geophysical methods, ERT and GPR.

1.2 Problem Statement

At a global scale, irrigation practices are responsible for 70%, 90% and 40% of freshwater abstraction, water consumption, and food production, respectively (Siebert et al., 2010). Previous study showed that only 55% of irrigation water is consumed by the plant, while the rest of water loss due to evaporation and percolation results in low irrigation efficiency (Chartzoulakis & Bertaki, 2015). This unsustainable practice has been reported to lead to rapid depletion of groundwater and surface water in many cultivated areas (Leng et al., 2015). The challenge becomes apparent particularly in semi-arid and arid regions (e.g. Saudi Arabia) where they are experiencing water-stress conditions while at the same time

highly relying on fossil groundwater to supply the irrigation water demand (Döll et al., 2014; Richey et al., 2015; Voss et al., 2013). Moreover, the global expansion of agriculture areas is expected to increase in the future to satisfy the rising food demand due to population growth. Considering the effect of climate change, it can be concluded that freshwater preservation (water security) and future food production (food security) would be threatened without sustainable irrigation water management.

Saudi Arabia has a desert arid climate characterized by low annual precipitation and higher evaporation. The freshwater resources in this country are considerably low. Saudi Arabia relies heavily on fossil groundwater resources and desalinized water to meet the water demand of multiple sectors, including the industrial, household, and agricultural sectors. Among them, the agricultural sector is considered as the biggest consumer of groundwater resources, accounting for around 85% of the total water supply in the kingdom. In addition, the Ministry of Environment, Water and Agriculture in Saudi Arabia has commenced the initial stage of two projects to plant 49 million fruit and lemon trees across different regions, which is part of the Saudi Green Initiative (Saudi Gazette, 2023). This initiative is anticipated to make a significant contribution to the sustainable cultivation and production of fruit crops, to achieve food security and sustainable development in the future. Within this context, implementing water saving irrigation schedule is crucial to conserve limited freshwater resources while at the same time ensuring agricultural productivity.

1.3 Research Gap and Questions

Understanding the spatial heterogeneity of subsurface properties is crucial to sustain agricultural productivity. Generally, soil heterogeneity is affected by biotics (root distribution, root water uptake) and abiotic factors (soil structure and texture) (Vereecken et al., 2008). In irrigated agricultural areas, soil moisture dynamic, influenced by irrigation water and precipitation, can be used as a proxy for soil heterogeneity (Vereecken et al., 2016a). Despite their importance, understanding the above factors in terms of spatial and temporal resolution is challenging to be achieved through traditional approaches such as excavation, soil pit or soil cores. These techniques are regarded as invasive approaches that are destructive, labor cost and time-consuming despite allowing direct observation of the root system. Invasive sampling might disturb the natural state of the root system and affect the processes within the root zone, thus altering the experimental results (Ehosioko et al., 2020). In addition, those practices can be considered impractical and inefficient over large areas due to heterogeneity of subsurface properties.

Nowadays, several non-invasive approaches, such as electrical resistivity and numerical simulation, can offer information on subsurface heterogeneity. However, only a few of the previous studies analyzing the soil-plant relationship using aforementioned techniques were conducted in semi-arid and temperate regions. Climate can be considered as an essential factor that can affect the soil-plant interface. To date, less attention has been given to area characterized by arid climate, particularly Saudi Arabia. There is still little understanding of the mechanism of soil-plant relationship under arid desert climate. In fact, knowledge of depth distribution and magnitude of soil-plant interaction as response to

warming temperature is beneficial for practical recommendation of agricultural water strategies.

Another non-invasive technique is GPR, known for its widespread use in coarse root investigation. In the context of agricultural crop, fine roots, conventionally defined as roots with a diameter of $\leq 2\text{mm}$, constitute the most dynamic and active component of belowground biomass, primarily responsible for absorbing water and mineral nutrients (Solly et al., 2018; Strand et al., 2008). Yet, the application of GPR to detect fine roots remains limited. Several studies suggest that GPR is not considered suitable for fine root detection (Hirano et al., 2009; Ow & Sim, 2012). This suggestion stems from the perception that common GPR studies for root detection typically aim to identify individual roots characteristics such as root biomass and diameter. This might be relevant for coarse root, but impractical for fine roots.

Therefore, this study addresses several research questions as mentioned below:

1. Where is the location and the geometry of the active root zone (the area where root water uptake occurs) in an arid climate?
2. What is the impact of seasonal variation on the root zone activities?
3. Can we replace the conventional way of measuring soil moisture by using local sensors by applying modern, non-invasive 3D and 4D geophysical methods?
4. Can we successfully use simulations such as HYDRUS and the geophysical survey results to estimate the root-water-uptake accurately?
5. What is the most suitable irrigation scenario for a lemon plantation supporting the Saudi Green Initiative program?

1.4 Objectives

The general objective of this study is to investigate of the hydrological dynamics in the soil-plant interface through non-invasive approaches under Saudi Arabia's arid climate in order to implement precision irrigation. Based on research questions, the objectives of this study are listed below:

- **To understand the spatial information of active root zone, this study aims to:**
 - a) Develop a non-invasive investigation protocol that can capture the root activity and distribution of active roots.
 - b) Analyze the pattern of active root water uptake zone by using time-lapse ERT.
 - c) Assess and confirm the vertical and lateral fine root distribution using GPR.
- **To determine the impact of seasonal variation on the root zone activities, this study aims to:**
 - a) Identify the diurnal pattern and magnitude of RWU under different seasonal variations using combined HYDRUS-1D and ERT.
- **To find the most suitable irrigation scenario, this study aims to:**
 - a) Designing the different irrigation scheduling scenarios using CROPWAT
 - b) Simulate soil water balance using HYDRUS-1D and ERT under different irrigation scenarios.
 - c) Analyze the water use efficiency under different irrigation scenarios.

1.5 Thesis Structure

The structure of this thesis consists of 8 chapters. Chapter one outlines the background of this study, the problem statement, the research gap and questions, and the objective of this study. Chapter two provides a literature review of different non-invasive approaches used in this study. Chapter three presents the site description, acquisition setup, data processing, and irrigation scenario simulation. The main results of this study are presented in chapters four, five, six and seven. In particular, chapter four discusses the primary findings from ERT acquisition. While chapter five presents the results of the GPR survey. Chapter six contains simulation results at an hourly time scale, and chapter seven explains the water balance modeling at a daily time scale. The final chapter (chapter eight) summarizes the key points of this study.

CHAPTER 2

LITERATURE REVIEW

2.1 Electrical Resistivity Tomography

The application of electrical resistivity (ER) in root zone study is generally to map the electrical properties of soils, conduction and polarization caused by inorganic constituents such as pore fluid, solid soil, air filled pore space, temperature, or organic constituents like organic matter and plant root (Cimpoiașu et al., 2020). ER is an active source geophysical method that injects low-frequency electrical current into the subsurface through pair of electrodes and measures the potential difference between the pair of electrodes (Al Hagrey, 2007a; Parsekian et al., 2015; Samouëlian et al., 2005). In particular, ER measures bulk soil resistivity and reciprocal of apparent soil electrical conductivity and requires good contact between soil and electrodes. Higher electrical contrast between soil matrix and heterogeneity would lead to easier detection and interpretation (Samouëlian et al., 2005).

The extension of ER is electrical resistivity tomography (ERT) or surface multielectrode method which is extensively used for soil-plant interaction studies. ERT is a high-resolution resistivity data that is processed using tomography imaging methods and capable to produce 2D, 3D and 4D of subsurface maps. A number of acquired data from different depths and locations can be provided simultaneously through ERT in order to improve 4D imaging (Calamita et al., 2012). The number of electrode and space between electrodes during acquisition will affect the coverage of subsurface information (Al Hagrey, 2007b; Calamita et al., 2012). In fact, ERT acquisition can involve hundreds or even thousands of electrodes. The electrode arrays of ERT can be permanently installed to minimize the effect

of each acquisition, therefore, it is favorable for non-invasive time-lapse operations (Nielson et al., 2021).

In time-lapse mode, ERT is sensitive to changes in soil electrical resistivity which is attributed to the factors controlling it, such as soil moisture. The changes in soil moisture variabilities detected by ERT can be utilized as a basis to interpret where root water uptake occurred (Cassiani et al., 2016; De Carlo et al., 2020; Mary et al., 2020; Vanella et al., 2018a), the extend of root plant (Garré et al., 2011; Mary et al., 2019a) and to distinguish old and dry root (Satriani et al., 2010). It can be stated that resistivity changes observed through ERT acquisition can be regarded as a proxy where active roots are present. However, the electrical resistivity ranges of soil and roots often overlap in most cases; moreover, ERT is less sensitive to roots than soil moisture, thus, identification of root biomass through ERT is considered not straightforward (Ehosioke et al., 2020; Mary et al., 2020).

One of the widely used applications of ERT in agricultural practice is to assess the spatiotemporal changes of SM since the variability of soil electrical resistivity is mainly controlled by the amount of water inside soil (Michot et al., 2003; Ranjy Roodposhti et al., 2019). Higher resistivity value indicates lower SM and vice versa. Using ERT would enable users to determine the spatial heterogeneity of SM, which would be impractical to measure with conventional and point-based measurement. Traditional techniques such as soil cores, neutron probes, or time domain reflectometry (TDR) are known for their robustness, however, they are disruptive to soil matrix and only applicable for local measurement.

In situ calibration of ERT is required to transform the measured bulk soil electrical conductivity into SM (Garré et al., 2011). The changes of SM variabilities detected by ERT can be utilized as an indicator to determine the active root zone where root water uptake occurred to investigate the impact of numerous irrigation treatments (Vanella et al., 2018b) and the extend of root plant (Garré et al., 2011; Mary et al., 2019b). For the root distribution study, old and dry root can be distinguished from active fine root based on resistivity values and size of resistivity anomalies (Satriani et al., 2010). Dry root is generally characterized by high resistivity, while active fine root has low resistivity.

2.2 Ground Penetrating Radar

One of the geophysical methods used for shallow subsurface investigation is the ground penetrating radar (GPR). A standard GPR unit consists of a control unit, transmitting and receiving antennas, and a display unit (Guo et al., 2013). In principle, GPR works by transmitting electromagnetic (EM) waves of specific frequencies into subsurface and records the scattered, reflected, and refracted waves (Davis & Annan, 1989; Klotzsche et al., 2018). The wave propagation of GPR is mainly influenced by dielectric permittivity, electrical conductivity and magnetic permeability from the medium which the wave travels (al Hagrey, 2007; Klotzsche et al., 2018). The attribute and location of target below surface can be identified by analyzing the travel times, amplitudes, and shape of reflected waves. The resolution of GPR depends on various factors, such as the antenna frequency, the EM characteristic of the medium and the penetration depth (Guo et al., 2013; Liang et al., 2020). The shape and size of the target, transmission characteristic of the medium, and surface feature will determine the type of antenna and signal frequency of GPR (Liang et al., 2020).

The profiling of GPR is similar to that of the seismic reflection method; however, the main difference is that GPR velocities decrease with depth while seismic velocities increase (Hanafy & al Hagrey, 2006). The decrease in GPR velocity is related to the increase of SM with depth as velocity is inversely proportional to SM, thus influencing the GPR signals (Hanafy & al Hagrey, 2006). GPR is most suitable to be implemented in areas composed of dry sandy soil. However, the performance of GPR will decrease in soil characterized by high water and clay content.

GPR has been seen as a viable tool to detect and quantify root system. Most dry soils and root systems can be considered as nearly non-magnetic and non-conductive media, hence electrical conductivity and magnetic permeability can be neglected (Al Hagrey, 2007b). Root system has different dielectric permittivity compared to soil, therefore allowing GPR to number, position, and size of mainly coarse roots. In general, GPR is suitable to detect roots with diameter more than 5 cm. However, finer roots with diameter of 0.5 cm or less could be also monitored (Liang et al., 2020; Xiao et al., 2021; X. Zhang et al., 2019), yet, number of studies that show the feasibility and accuracy of this method to detect fine root (<2 mm in diameter) is still limited (X. Liu et al., 2018).

GPR typically generates distinctive hyperbolic reflection in the radar profile upon root detection (Hruska et al., 1999; Molon et al., 2017; Satriani et al., 2010; X. Zhang et al., 2019). Live root is characterized by well-defined hyperbola compared to dead root that has non-well-developed hyperbola (X. Zhang et al., 2019). However, it is difficult to identify a single root in dense root system as GPR will generate one huge hyperbola (Liang et al., 2020). In general, GPR has several advantages for root study: (1) this technique is a non-destructive that permits long-term and repeated measurement; (2) GPR can identify and

localize root density; (3) it can detect root density rapidly at large spatial scale; (4) GPR can characterize live and dead roots (Cui et al., 2021; X. Zhang et al., 2019). Despite showing promising results, the successful application of GPR in root study can be considered as a site-specific. Several factors affect the accuracy of GPR acquisition, including soil properties, crop type, frequency of antenna, or signal filter process (Guo et al., 2013).

2.3 Hydrological Simulation

Water fluxes in an unsaturated porous medium connecting surface water and groundwater is one of the most complex natural processes in nature. Understanding these processes is essential and vital for hydrology, agricultural and environmental studies. A number of models, ranging from semi-empirical, empirical and physical-based models are commonly utilized to understand the dynamic of water fluxes in the vadose zone (Ma et al., 2010; Mishra et al., 2003). Semi-empirical and empirical models are commonly derived from laboratory or field analysis in the simple equation form (Ma et al., 2010; Mishra et al., 2003). Compared to semi-empirical and empirical models, physical-based model can describe detailed hydrological processes (Ma et al., 2010). Among the physical-based model, Richard's equation, which combine the continuity equation with Darcy law is the most commonly employed. This equation can be written in various forms. From the context of soil water fluxes, by incorporating a sink term accounting for root water uptake process, Richard's equation can be written as:

$$\frac{\partial \theta(h_w)}{\partial t} = \frac{\partial}{\partial z} \left[k(h_w) \left(\frac{\partial h_w}{\partial z} + 1 \right) \right] - S(z) \quad (1)$$

where θ is the volumetric water content ($L^3 L^{-3}$), t is time (T), z is the vertical coordinate positive upward (L), $k(\theta)$ is the unsaturated soil hydraulic conductivity (LT^{-1}), h_w is the soil-water pressure head (L), and S is the sink term representing root water uptake.

Richards' equation represents hydrological flow caused by gravity and capillary actions in unsaturated porous medium where the non-wetting phase flow such as air can be ignored (Farthing & Ogden, 2017). The physical properties of the medium are described as nonlinear coefficients in this equation (Farthing & Ogden, 2017). Due to its nonlinearity, Richard's equation remains challenging to be solved analytically (Ma et al., 2010; Vereecken et al., 2016b). Many practical situations need numerical solutions like finite difference, finite element and boundary element to solve Richard's equation (Farthing & Ogden, 2017; Feddes et al., 1988). Several hydrological processes have been successfully simulated based on Richards' equation, such as infiltration (Fan et al., 2018; Ma et al., 2010) and root water uptake (Broadbridge et al., 2017; Couvreur et al., 2012). Despite being successfully utilized for numerous applications, Richards' equation is not applicable to all types of soil, particularly soil with high organic matter or clay contents (Vereecken et al., 2016b).

HYDRUS is the most popular software package for numerically solving Richard's equation based on finite element models. HYDRUS can simulate water, heat, and dissolved substance movement in unsaturated porous medium in 1D, 2D, and 3D (Šimůnek, Genuchten, et al., 2016b). This package is often preferred due to its simplicity compared

to other models and requires few input parameters. In addition, the results obtained by HYDRUS are satisfactory as reported by several studies (Autovino et al., 2018; Er-Raki et al., 2021; Ghazouani et al., 2019). In soil and agricultural studies, HYDRUS is usually utilized to simulate soil water balance components, including infiltration, transpiration, soil evaporation, root water uptake and deep percolation.

CHAPTER 3

DATA AND METHOD

3.1. Site Description and Experimental Design

The experiment was carried out in a wooden box (192x192x153 cm³) filled with soil, containing 99.5% sand, and the remaining material was silt (0.5%). This is a typical soil type for Saudi Arabia, especially in the broader area of East Province and Riyadh. Based on Liu et al. (Y. Liu et al., 2022a), the soil can be considered sandy soil with 5-12% soil moisture. It has to be mentioned that to increase the fertility of this highly sandy soil, compost as a soil amendment was added and enough time (4 months) was applied before starting the experiment to achieve proper maturation of the mixed soil within the tank. Additionally, the wooden box was constructed without any metallic object (such as nails) to ensure favors conditions for conducting geoelectrical and GPR measurements to detect and characterize the root zone.

The site where the controlled experiment was set up, is located at King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia, which is characterized by a desert arid ecosystem. The mean annual temperature is 26.4°C, while the average yearly precipitation is 84 mm. July is the hottest month in this area, with an average high of 42°C and a low of 29°C. Dhahran has extreme seasonal variation in terms of perceived humidity, where the muggier period occurs from May to November. During the 7-months of study period (March – September 2023), no precipitation event was recorded.

Based on the green initiative in Saudi Arabia and its priorities, a citrus plant was selected to model the RWU. Citrus is widely acknowledged as a crucial horticultural crop in the global agricultural sector, with production spanning across 140 countries (Ziogas et al., 2021). Citrus trees yield various fruits, including significant agricultural commodities like oranges, lemons, grapefruits, pomelos, and limes. Citrus cultivation covers a total area of 10,072,197.00 hectares worldwide, producing 58,490,986.00 tons in 2020 (Fao, 2021). The majority of citrus-growing regions experience arid and sweltering summer conditions. Effective management of citrus irrigation and nutrient levels is crucial, particularly in regions where water resources are limited.

For our experimental work, a 1-year-old and 2.5m high citrus (lemon) tree was planted and monitored for one year. Citrus plants possess a superficial root system. Directing irrigation towards the efficient root zone is crucial, minimizing the amount of water that drains beyond it. Most lemon tree roots primarily reside within the uppermost 60 centimeters of soil, but the optimal root zone typically lies within the uppermost 30 to 40 cm of soil, with variations depending on the specific soil composition (Fares & Alva, 2000; Paramasivam et al., 2001; Parsons & Boman, 1969). Thus, the target area for monitoring the root zone and characterizing its soil moisture is limited to the upper 50cm, with the highest density of the root zone expected at a depth of 30-40 cm (Yu et al., 2007).

Conventional flood irrigation was used to water the plant during this experimental study. The TDS of domestic water used to regularly irrigate the crop was measured at around 500-700 ppm. The amount of irrigation water was determined based on the FAO-56 method (Allen et al., 1998). This method calculates crop water requirement (ET_c) by multiplying reference evapotranspiration (ET_o) with crop coefficient (K_c). ET_o is calculated according

to the Food and Agriculture Organization of the United Nations (FAO) Penman-Monteith equation, while the seasonal K_c for specific crops can be obtained from the FAO database. ETo requires some meteorological parameters such as temperature, humidity, wind, sunshine, and net radiation. In this study, the meteorological dataset to calculate reference evapotranspiration was derived by CLIMWAT based on historical record in Dhahran observation station. CLIMWAT is a climatic database of more than 5000 stations worldwide that is commonly utilized in combination with CROPWAT to calculate crop water requirement. During the observation period (March to September 2023), the tree was kept well-watered through daily irrigation estimated by CROPWAT-CLIMWAT.

3.2. ERT Measurement

3.2.1. Experimental Setup

Eight wooden sticks were used to simulate the boreholes with 24 installed electrodes on each. The boreholes were installed, ensuring verticality and exact spatial location to apply the correct geometric factors during the processing. A reference resistivity measurement was acquired in January 2023 (T0) to ensure that a layered and semi-homogenized system was created before planting the lemon tree. A period of 1 month (February) was given to the plant to adapt to the new environment (soil and environmental conditions) before the geophysical measurements were initiated. Seven time-lapsed 3D high-resolution DC datasets were collected from March – September 2023 (T1-T7). During the measuring period, the temperature during the day, was varied from 27°C in March, to the top of 49°C during July and an average of 38°C during September 2023. Even, the plant was irrigated

with the proper quantity and quality of water during the experiment, after the thermal shock of the summer, the lemon tree was dried out after the end of September, and as a result, we had to conclude the 4D DC experiment.

3.2.2. ERT Imaging

The electrical resistivity setup involved the installation of eight borehole-electrodes, each equipped with 24 electrodes with 5 cm intervals and a total of 192, strategically placed to cover the entire 3D space within the root zone, as shown in Figure 1. A distance of about 50cm from the sides and 19cm from the bottom of the box was kept during the installation of the geoelectrical array to minimize the side effects during the collection and the subsequent processing of the acquired data. Maintaining the integrity of the electrode positions was vital for estimating the geometrical factor correctly, which is essential for accurate data interpretation. The Syscal Pro acquisition system was used to acquire the electrical data, and the Res3dinv software was applied to process the raw data and produce the final 3D and 4D tomographic sections.

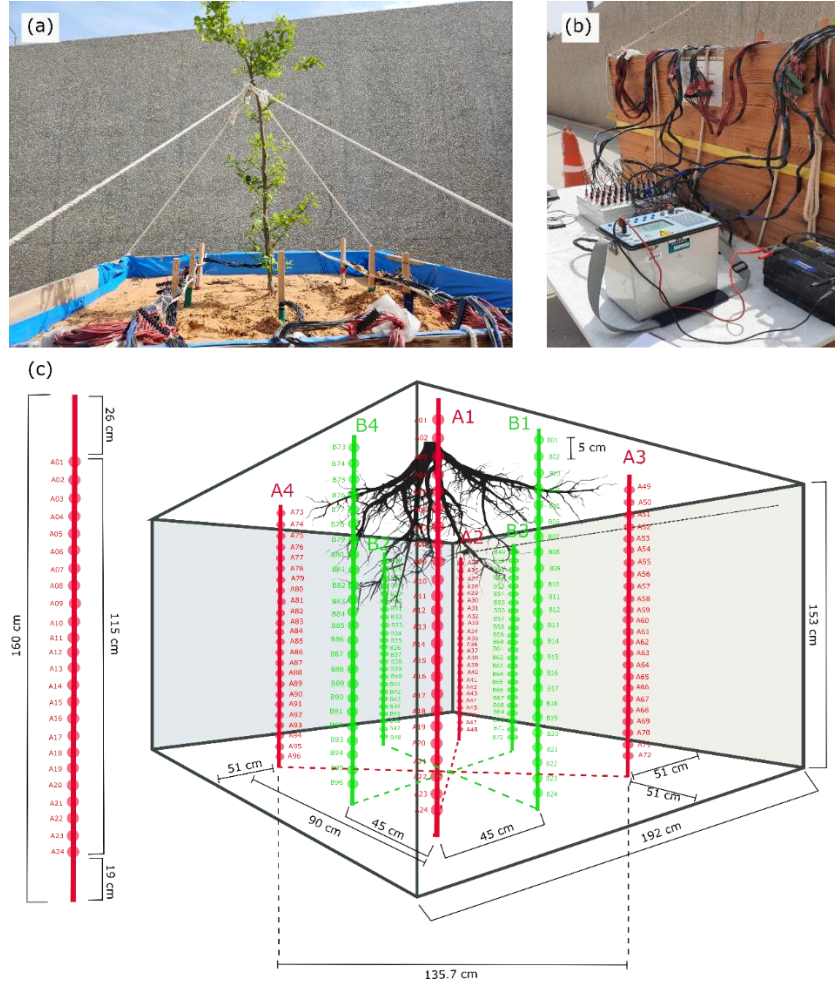


Figure 1 (a) 3D wooden tank with plant, (b) ERI acquisition system and the custom-made multiplexer for all 96-channels are shown, and (c) the layout of the 3D cross hole geoelectrical experiment where the eight ERI boreholes (A1-4 and B1-4) are shown.

In order to utilize the 96-channel Syscal Pro system and collect more data, thus improving the vertical and spatial resolution of the collected data, two sets of data using 96 electrodes from groups A and B boreholes, were acquired using two specially designed customized boxes, as depicted in Figure 1b. Later, these two (A and B group) 3D geoelectrical data were merged to be processed simultaneously. This custom setup allowed us to regulate the acquisition protocol meticulously, ensuring consistency and reliability across all measurements.

The choice of the acquisition protocol played a pivotal role in our study. We opted for specific protocols to enhance resolution and speed. The selected protocols were instrumental in achieving a higher resolution of the collected data while expediting the measurement process, which is crucial for effectively capturing dynamic processes in the root zone. This study utilized the dipole-dipole (DD) diagonal electrode array for the borehole pairs A1-A2, A3-A4, B1-B2, and B3-B4 to achieve accurate horizontal and lateral resolution of the root zone (Figure 2). The objective was to observe variations in soil moisture across different areas. The tomographic array's electrode configurations provide enhanced sensitivity and resolution to subsurface structures in two dimensions. These configurations have been extensively described in various publications, such as (Hinojosa et al., 2022; Kirmizakis et al., 2023; Simyrdanis et al., 2018; Soupios et al., 2007).

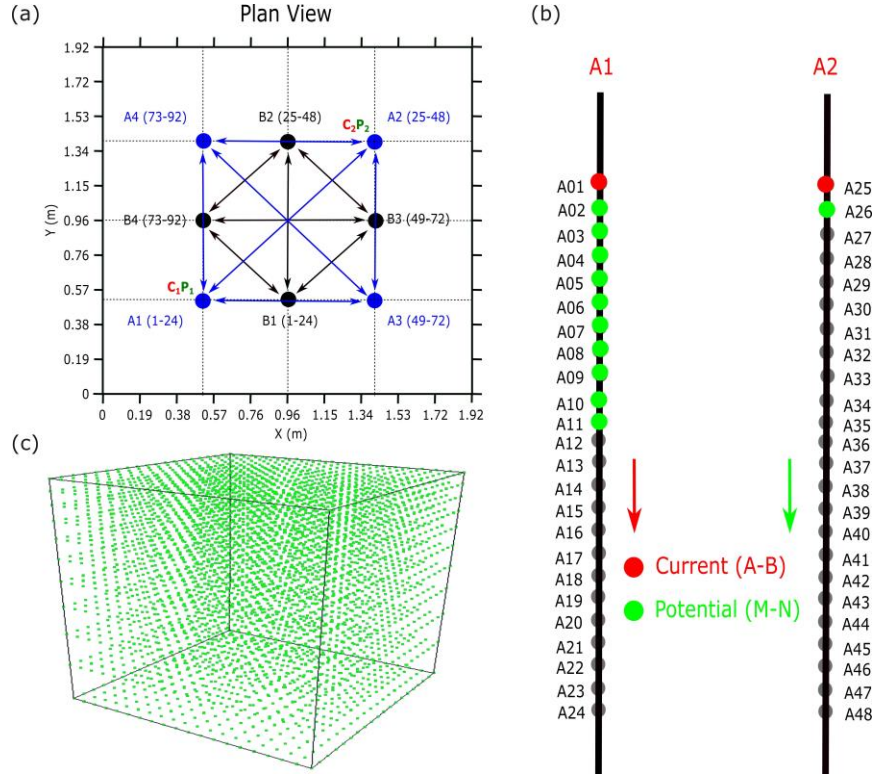


Figure 2. (a) The plan view of the experimental geometry is presented. The distances of the boreholes between them and from the sides of the tank are also shown. The cross borehole measurements were acquired between all possible borehole pairs (black and blue lines) and all these data were combined and used for the final 3D inversion. (b) A sketch of the cross section of the experimental geometry is shown where the current (C-red dots) and potential (P-green dots) electrodes were placed in each borehole. The optimum CPs combinations we used. Reciprocity was also ensured. (c) The coverage density of the study area by data is shown.

3.2.3. 3D/4D Modeling and Inversion

This study employed readily accessible Res3dinvx64 Professional modeling and inversion software to process the acquired 3D and time-lapse (4D) DC data. The program's inversion routine is derived from the smoothness-constrained least-squares method, as Loke et al. (2003) described. The fundamental approach of the smoothness-constrained least-squares method is derived from the subsequent equation (2):

$$(J^T J + \lambda F) \Delta q_k = J^T g - \lambda F q_{k-1} \quad (2)$$

where, $F = \alpha_x C_x^T C_x + \alpha_y C_y^T C_y + \alpha_z C_z^T C_z$, C_x and C_y are the horizontal roughness filters, C_z is the vertical roughness filter, $\alpha_x, \alpha_y, \alpha_z$ are the weights for roughness filters, g is the data misfit vector, J is the Jacobian matrix of partial derivatives and J^T the transpose of the Jacobian, λ is the damping factor, q is the model perturbation vector and k is the iteration number.

An advantage of this method is the ability to customize the damping factor and roughness filters to accommodate various data types. This program employs the Gauss-Newton method, which involves recalculating the Jacobian matrix of partial derivatives after each iteration, as described by Loke and Dahlin (2002). In addition to the aforementioned fundamental smoothness-constrained approach, alternative variations can also be utilized. An example of an effective model inversion method is the L1 norm inversion method, which tends to generate models with well-defined boundaries (Loke et al., 2003; (Loke, 2004; Loke et al., 2013; Loke & Barker, 1996). The inversion program discretizes the subsurface into multiple rectangular prisms and aims to ascertain the resistivity values of these prisms to minimize the discrepancy between the calculated and observed apparent resistivity values, while adhering to specified constraints. The inversion process begins with an initial homogeneous q model, typically represented by the average measured apparent resistivity (ρ_a) values. It then calculates the forward ρ_a model and compares it to the measured ρ_a model. For the calculation of the ρ_a model, the finite-difference or finite-element method can be used. The finite-difference method was applied for this application since it is faster, requires less computer memory, and the data set does not contain topography. Based on the comparison between observed/measured and calculated at each

iteration, the initial model is subsequently adjusted and corrected. The root-mean-squared (RMS) error is used to quantify the fitting of the final model as the difference between measured and calculated resistivities. The model that exhibits the minimum RMS error can occasionally show significant and implausible fluctuations in the resistivity values and may not consistently be considered the most optimal model from a geological standpoint. The process is repeated until the root mean square (RMS) misfit reaches a value below a predefined threshold, such as the average error in the data. Typically, it is advisable to select the model at the iteration where the root mean square (RMS) error stabilizes.

For the 3D processing, meticulous data refinement was employed to ensure the accuracy and reliability of our results. Initially, we removed data points with deviation > 10 , $I < 0.01$ Amp, and negative apparent resistivity < 0 Ohm.m from the raw data, as outlined in Table 1. Data points with deviation greater than 10% often indicate noise or errors in measurements, while current intensity is crucial for the accuracy of the resistivity measurements. By applying a threshold of $I < 0.01$ Amp we ensure that only data with sufficient signal strength are considered. Furthermore, the import file precisely defined the tank boundaries, providing a clear spatial context.

A damping factor with a depth sets at 1.010 was implemented to optimize the processing. Given that the resolution of the resistivity method decreases exponentially as depth increases, it's common practice to incrementally raise the damping factor for each subsequent deeper layer during the least-squares inversion method. This step is crucial for ensuring the stability of the inversion process, with the damping factor typically being augmented by a factor ranging from 1.01 to 1.20 for each additional layer. A robust data constraint using the L1-norm with a cutoff factor 0.1 was applied to set a threshold that

determines the extent to which data points are considered outliers or noise and thus subject to being downweighted or removed from the analysis. When a cutoff factor of 0.1 is applied in this context, it means that data points with deviations from the median measurement that are greater than this threshold are considered less reliable or significant. This cutoff value helps in minimizing the impact of highly variable or anomalous data on the imaging results, enhancing the robustness and accuracy of the resistivity analysis. By selectively downweighting or excluding these points, the process aims to produce a clearer, more consistent representation of subsurface resistivities, improving the quality of the imaging outcomes.

A slight reduction effect was introduced to mitigate the impact of side model cells and prevent unusually high or low resistivity values at the corners, especially when employing the L1-norm model constraint. After the filtering, less than 16% of the data (noisy or low-quality data) were removed, and the rest were used for further processing. Inversion parameters remained consistent with those outlined in 3D processing. Furthermore, sensitivity values were utilized to minimize resistivity variations near the borehole electrodes, ensuring a more accurate representation of the electrical properties. The final 3D resistivity models for the different ERI experiments were resulted after an average of 11 iterations with a normal smoothness-constrained RMS (L2-norm) and robust/blocky L1-norm of 8.7% and 8.67%, respectively (Table 1).

Table 1 Summary of ERI's data acquisition and processing parameters for all individual data sets during 3D individual dataset processing is presented.

Parameters	T1	T2	T3	T4	T5	T6	T7
Time interval (days)	0	18	51	69	109	150	186
Electrode array	DD	DD	DD	DD	DD	DD	DD
Electrode No.	192	192	192	192	192	192	192
Quadripoles (prior filtering)	18540	18540	18540	18540	18540	18540	18540
Quadripoles (after filtering)	16618	16521	17296	16606	13785	13582	14861
% of removal after filtering	10.36	10.89	6.71	10.43	25.64	26.74	19.84
Iterations No.	12	7	12	16	12	8	10
RMS (%)	8.8	10.2	10.2	5.98	7.0	9.6	9.12
L1-norm (%)	8.89	10.23	10.22	5.59	7.0	9.61	9.13

For the time-lapse (4D) inversion, the separate 3D data files acquired at different times were combined into a single time-lapse data file, using the same survey grid. The same constraints for deviation, current (Amp), and apparent resistivity as in 3D processing were applied to the raw data. Additionally, all data points had to be matched across different time periods, leading to the removal of even high-quality points for most of the time periods (Table 2). Proper inversion (regularization) parameters, such as damping and smoothing, were applied for the inversion of the time-lapse data files. Temporal and spatial roughness filters were used, and the optimum damping factor, based on data error, was applied to the roughness (temporal and spatial) filter, which is typically reduced after each iteration. Furthermore, the import file precisely defined the tank boundaries, providing a clear spatial context. A slight reduction effect was introduced to mitigate the impact of side model cells

and prevent unusually high or low resistivity values at the corners, especially when employing the L1-norm model constraint.

The smoothness-constrained least-squares optimization is modified to the subsequent form for time-lapse data, Eq. (3):

$$[J^T J + \lambda (F + \alpha M^T R_t M)] \Delta q_k = J^T g_k - \lambda (F + \alpha M^T R_t M) q_{k-1} \quad (3)$$

where, R_t is the model resolution matrix: $(J^T J + \lambda F)^{-1} J^T J$ and M are the model parameters.

The model resolution values of the model blocks are determined by the diagonal elements of this matrix. The model resolution matrix R can be regarded as a filter that the inversion method uses to determine the subsurface resistivity (Day-Lewis et al., 2004). The 'temporal roughness filter' determines the damping factor α in the equation above, which aims to reduce temporal variations in resistivity across various time models (Loke et al., 2014). The temporal damping factor can be consistent for each iteration or decrease with iterations following the spatial damping factor λ . The L2 (smooth) and L1 (blocky) roughness constraints to the time-lapse models were applied, as described by Loke et al. (2014).

After filtering and applying the constraints mentioned above for the 4D inversion, 48.60% of the data were removed, and the rest were used for further processing. Inversion and sensitivity parameters remained consistent with those outlined in 3D processing. The final 4D resistivity models for the different ERI experiments resulted after an average of 5 iterations with an average smooth RMS (L2-norm) and L1-norm (blocky model) of 15.5% and 26.39%, respectively (Table 2).

Table 2 A summary of ERI's data acquisition and processing parameters for all individual data sets during 4D data processing is presented.

Parameters	T1	T2	T3	T4	T5	T6	T7
Time interval (days)	0	18	51	69	109	150	186
Electrode array	DD	DD	DD	DD	DD	DD	DD
Electrode No.	192	192	192	192	192	192	192
Quadripoles (prior filtering)	18540	18540	18540	18540	18540	18540	18540
Quadripoles (after filtering)	9012	9012	9012	9012	9012	9012	9012
% of removal after filtering	48.60						
Iterations No.	5						
RMS (%)	15.5						
L1-norm (%)	26.39						

Finally, to image the changes in the estimated 4D model within the 3D volume and for all time periods, the model resistivity change was applied in Res3DInvx64 software. This option allows the user to choose the formula that will be used to calculate the percentage change in the resistivity of the model between two-time series models. The logarithmic or the relative change in resistivity can be applied when larger or small changes are expected, respectively. To image the percentage change in resistivity for this experiment, the relative change was selected since only slight changes in resistivity within the period of 7 months are expected to be detected in the root zone. For this, the percentage changes between T2-T1, T3-T1, ..., T7-T1 were calculated by dividing the change in resistivity for each time period by the resistivity of the initial (T1) time series model.

3.3. GPR Acquisition

3.3.1. Field Procedure

The Subsurface Interface Radar (SIR) System-4000 developed by Geophysical Survey Systems, Inc (USA) with a 400 MHz shielded antenna was employed for acquisition using the wheel mode data collection to ensure accurate offset measurements. The choice of frequency during GPR acquisition could affect the depth of penetration and resolution. A higher frequency will provide high resolution with limited depth of investigation, while a lower frequency offers deeper penetration with lower resolution (Hruska et al., 1999). Since our objective is to determine the area where roots exist regardless of their physical characteristics and after conducting different GPR measurements using various antennas (frequencies), the frequency of 400 MHz was selected. We expected that this frequency could achieve the desired depth of investigation while detecting the area of the roots system.

The acquisition was carried out on September 18, 2023, under two distinct conditions: dry soil and wet soil. The first dataset was obtained under dry-soil conditions and was recorded in the morning when the soil was dry. Subsequently, the second dataset was conducted in the afternoon, 30 minutes after watering the soil with approximately 80 liters of water until the soil was fully saturated. This was indicated by water exceeding from the bottom of the woody box, thus representing the wet soil condition.

GPR datasets were acquired with an acquisition time range of 40.0 ns (dry-soil condition) and 50.0 ns (wet-soil condition). Each scan comprised 512 samples. To gather comprehensive data, a total of 71 horizontal profiles, each 1.5m long with a profile interval

of 1.5 cm within the survey area ($1.5 \times 1.05 \text{ m}^2$) were acquired. This approach facilitated the generation of a 3D dataset, commonly referred to as a data cube (Figure 3).

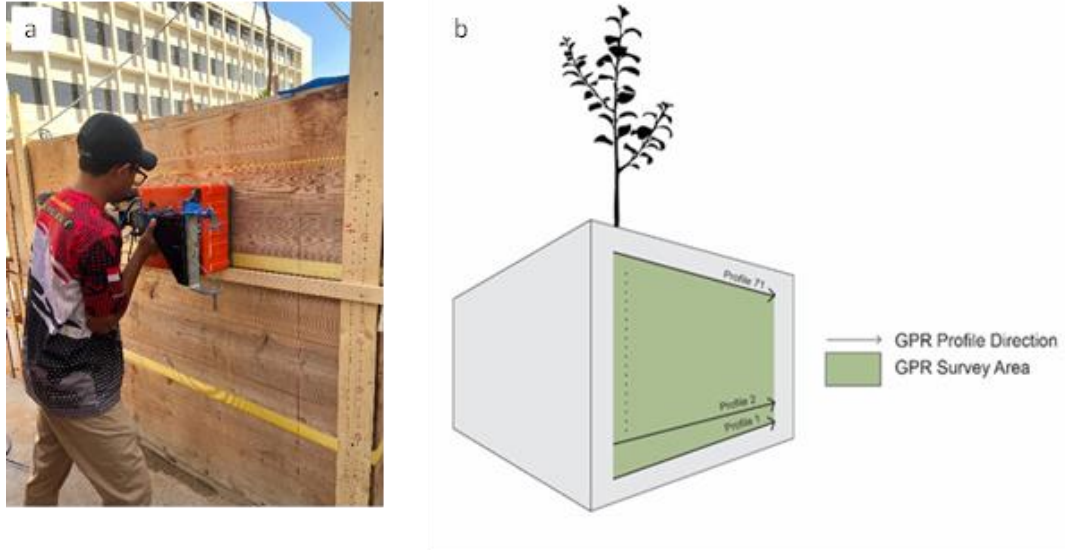


Figure 3. (a) The procedure to collect GPR dataset using the SIR-4000 system with the 400 MHz antenna at experimental site and (b) the pathway of GPR acquisition.

3.3.2. Data Processing

This study utilized the Reflexw and Voxler software for data processing and visualization, respectively. Basic processing steps of GPR were applied to enhance the signal-to-noise ratio of the recorded data. These steps involve dewow, automatic gain control (AGC), butterworth filter, static correction, and running average. GPR data usually involve low-frequency noise caused early wave arrivals, resulting in signal-saturation. Hence, to eliminate very low frequency induced on the trace, dewow or signal saturation correction was applied with a maximal window of 80 ns. Since radar attenuation might disturb the image of radargram, AGC (15 ns of window size) was utilized for amplitude decay

compensation. This attenuation could be derived from antenna radiation, reflection, refraction, and conductive loss.

In addition, a second-order bandpass Butterworth filter (0-750 GHz) was applied to remove low-frequency artifacts and high-frequency noise. Static correction (-7 ns) was performed to compensate for the time delay of the first arrivals. Thus, the direct wave effect can be eliminated, and zero-time correction can be achieved. Subsequently, the zero-time corresponded to the position of antenna in the survey area. Finally, in order to enhance certain frequencies and features and reduce random noises, a running average filter was applied. The three-dimensional image of fine roots distribution was constructed based on a manual delineation of reflected waves from each GPR profile. Examples of raw and processed GPR radargram after applying basic processing steps from different profiles are depicted in Figures 4a and 4b, respectively.

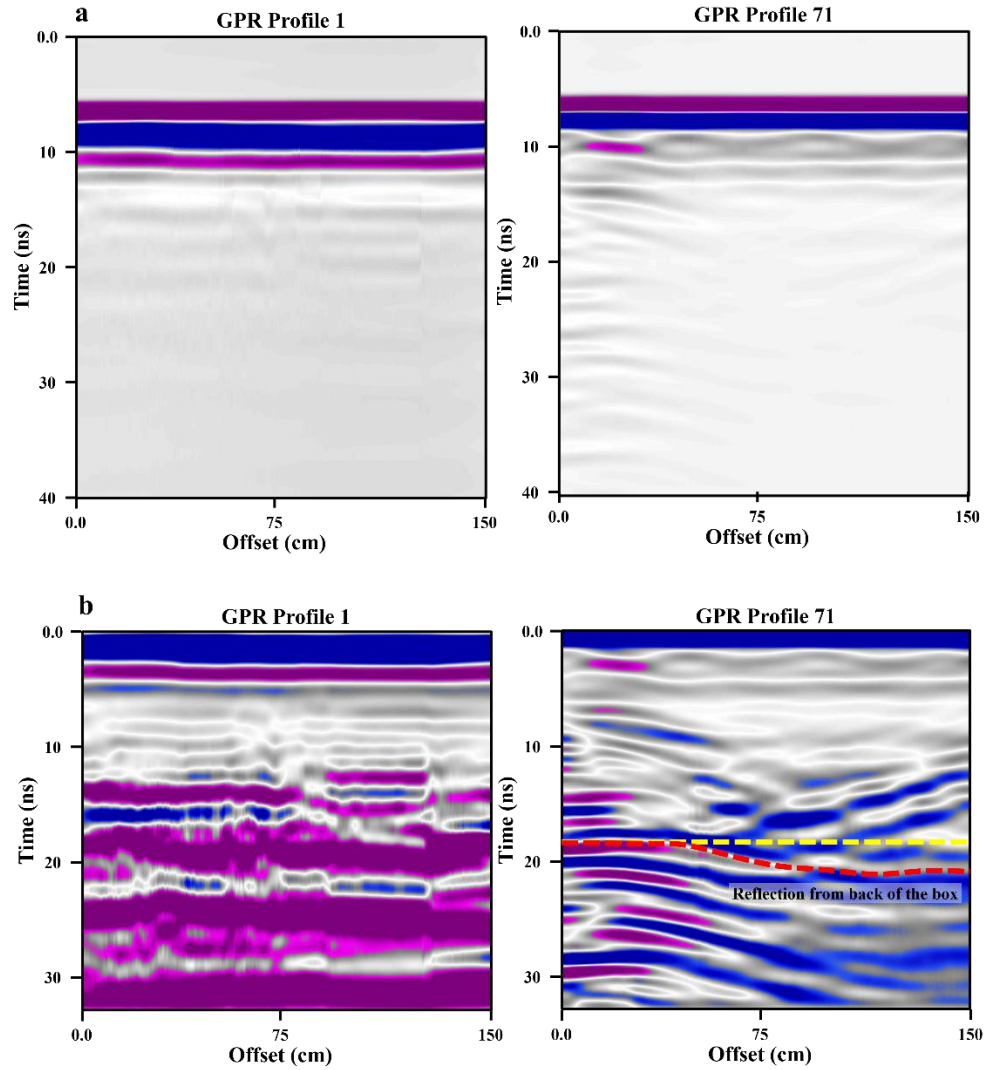


Figure 4. (a) Raw data of the first and the last profiles of radargram recorded from SIR system-4000 with an antenna of 400 MHz. (b) The processed radargram after using the processing steps listed in the text. The first profile is at the bottom of the wooden box, while the last is near the soil surface where the roots exist. The yellow dashed line is the actual boundary of the box, while the red dashed line represents reflection from the back of the box

3.4. Hydrological Modeling

This study utilized one of the most popular numerical packages, HYDRUS-1D software, to simulate the soil water balance in the root zone. Subsequently, the root water uptake and deep percolation can be determined. The input data of HYDRUS-1D software consists of

time constant data and time variable data. Soil hydraulic parameter and initial soil water content represent time-constant data. While time variable data are composed by the atmospheric boundary condition with runoff and variable pressure head representing upper boundary condition and lower boundary condition, respectively. Soil hydraulic parameters such as saturated water content, residual water content, and empirical shape factor in the water retention function are estimated using ROSSETA program for input of HYDRUS software. The atmospheric boundary condition is represented by potential transpiration (T_p) and potential soil evaporation (E_p). Leaf area index (LAI) and reference evapotranspiration (E_{To}) are used as basis to calculate T_p and E_p . Figure 5 below shows the flowchart of soil water balance estimation using HYDRUS-1D software.

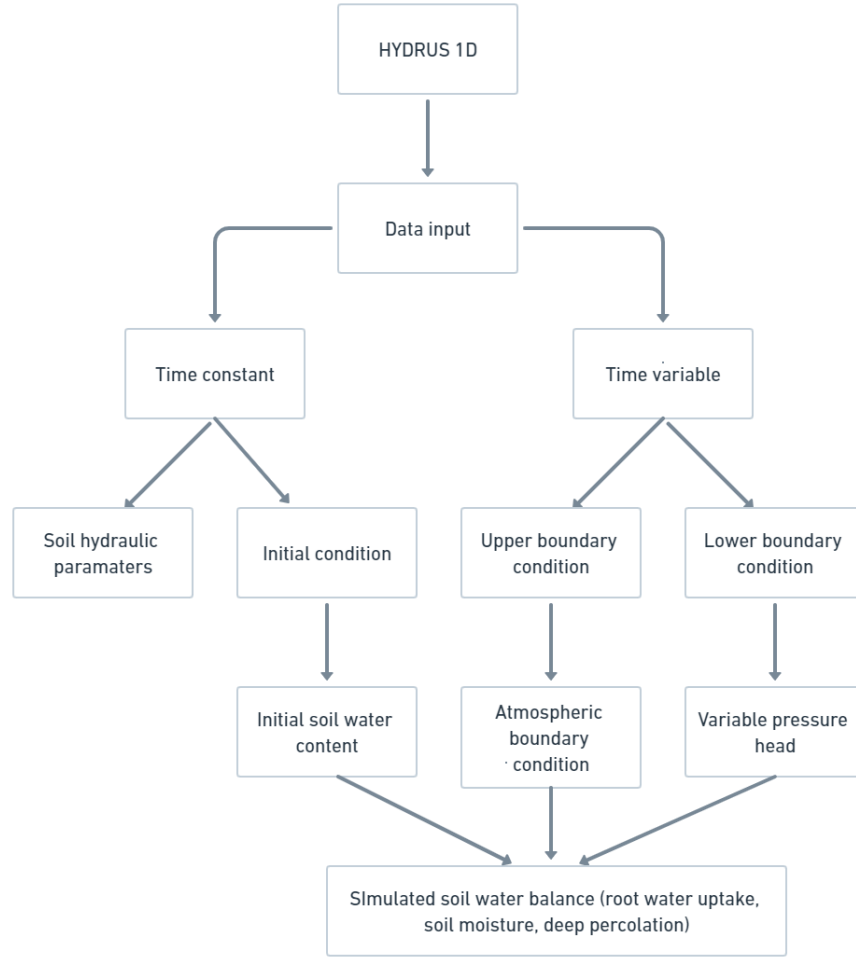


Figure 5. Flow chart of soil water balance measurement using HYDRUS-1D (Iqbal et al., 2020)

The van Genuchten-Mualem constitutive relationships (van Genuchten, 1980) were employed to determine the soil water retention curve as shown below (Eq. 4):

$$\theta(h) = \begin{cases} \theta_r \frac{\theta_s - \theta_r}{[1 + |\alpha h|^n]^m} & h < 0 \\ \theta_s & h \geq 0 \end{cases}$$

$$K(h) = K_s S_e^l \left[1 - (1 - S_e^{1/m})^m \right]^2, \quad (4)$$

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r}$$

where, θ_r is the residual water content ($\text{cm}^3 \text{ cm}^{-3}$), θ_s is the saturated water content ($\text{cm}^3 \text{ cm}^{-3}$), α , n and l are empirical parameters, S_e is the effective saturation, and K_s is the saturated hydraulic conductivity (cm/d).

The root water uptake process in HYDRUS 1D is simulated using the Feddes model (Feddes et al., 1978) without considering the osmotic stress that can be expressed as follows (Eq. 5):

$$S(z, t) = \alpha(h, z) \beta(z) T_p$$

$$\alpha(h, z) = \begin{cases} 1 & h_1 \leq h \leq 0 \\ \frac{h-h_2}{h_2-h_1} & h_2 \leq h \leq h_1, \\ 0 & h \leq h_2 \end{cases} \quad (5)$$

where, $\alpha(h, z)$ is the water stress response function, $\beta(z)$ is the standardized RWU distribution function, T_p is defined as the potential crop transpiration rate, while h_1 and h_2 are the soil water potential at which RWU rate decreases from 1 cm and decreases to 0 cm, respectively. In this study, the parameters of the lemon RWU configuration provided by HYDRUS 1D were selected. The model was also calibrated through soil hydraulic parameters (Šimůnek, van Genuchten, et al., 2016).

3.4.1. Boundary Conditions

The upper boundary conditions were assigned as atmosphere boundary conditions with surface runoff since the soil profile was subjected to rainfall, evaporation, runoff and root water uptake and deep drainage (Diongue et al., 2022). While the lower boundary condition was defined as a free drainage since this measurement was conducted into a permeable bottom side experimental box. Based on the above, the water table was far below the root zone which represents the real condition in Saudi Arabia. Results from geophysical acquisition were utilized to determine the hydrological initial conditions.

For daily time step simulation, the potential crop transpiration (T_p) and potential soil evaporation (E_p) were calculated using following equation:

$$T_p = ET_c(1 - e^{-k*LAI}) \quad 6$$

$$T_p = ET_c * e^{-k*LAI} \quad 7$$

Where E_{To} is reference evapotranspiration according to FAO-56 Penman equation (Allen et al, 1998), LAI is a leaf area index (dimensionless) while k is the global solar radiation coefficient. The k value in this study was set to 0.38 following Hu et al (2017). In this study, E_{To} was calculated at monthly basis based on ERA5-Land dataset. ERA5-Land is a reanalysis dataset developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) that combines observations data across the world and provides reliable estimates of historical climate

3.4.2. Irrigation Scenario Simulation

The irrigation scenario was estimated using CROPWAT 8.0. The United Nations Food and Agriculture Organization (FAO) developed this software and is commonly used to estimate crop water requirements and manage irrigation schedules. The irrigation scenarios consisted of four different irrigation intervals: I_1 , I_2 , I_3 , and I_4 . I_1 is the existing irrigation treatment, where the crop was supplied by daily irrigation. I_2 , I_3 and I_4 represent the interval of 1 day, 2 days and 3 days, respectively, after the last irrigation. The water amount for scenarios I_2 , I_3 and I_4 were adjusted according to crop water requirements simulated by CROPWAT.

CHAPTER 4

NON-INVASIVE 3D AND 4D ROOT ZONE MONITORING: A CASE STUDY USING ELECTRICAL RESISTIVITY IMAGING

4.1. Electrical Resistivity Imaging

The apparent-resistivity data sets were inverted using a total of 15,609 data points (quadripoles, Table 1) to characterize the 3D model for an area of 0.9315 m³ (W:90cm X D:90cm X H:115cm). The resulting individual resistivity models from the different time phases show similar structural characteristics to each other, indicating a high level of reliability in the technique. Figure 6 displays the 3D inversion outcomes after the irrigation of the individual datasets (T1-T7 from March 2023 – September 2023) for 5 different depths, 3-5 cm, 9-12 cm, 17-22 cm, 28-34 cm, and 42-51 cm. During the experiment and a few hours before the measurements, the plant and the area near the boreholes were watered to ensure good contact resistance (always less than 30 kOhm), minimizing the noise to the recorded data. The inversion models demonstrate a satisfactory fitting with the measured data since the root mean square (RMS) errors varied from 5.58-10.20 %. The dashed line depicts the expected spatial distribution of the root zone. For all the tomographic images, the same resistivity scale was used to be able to compare the resulting images.

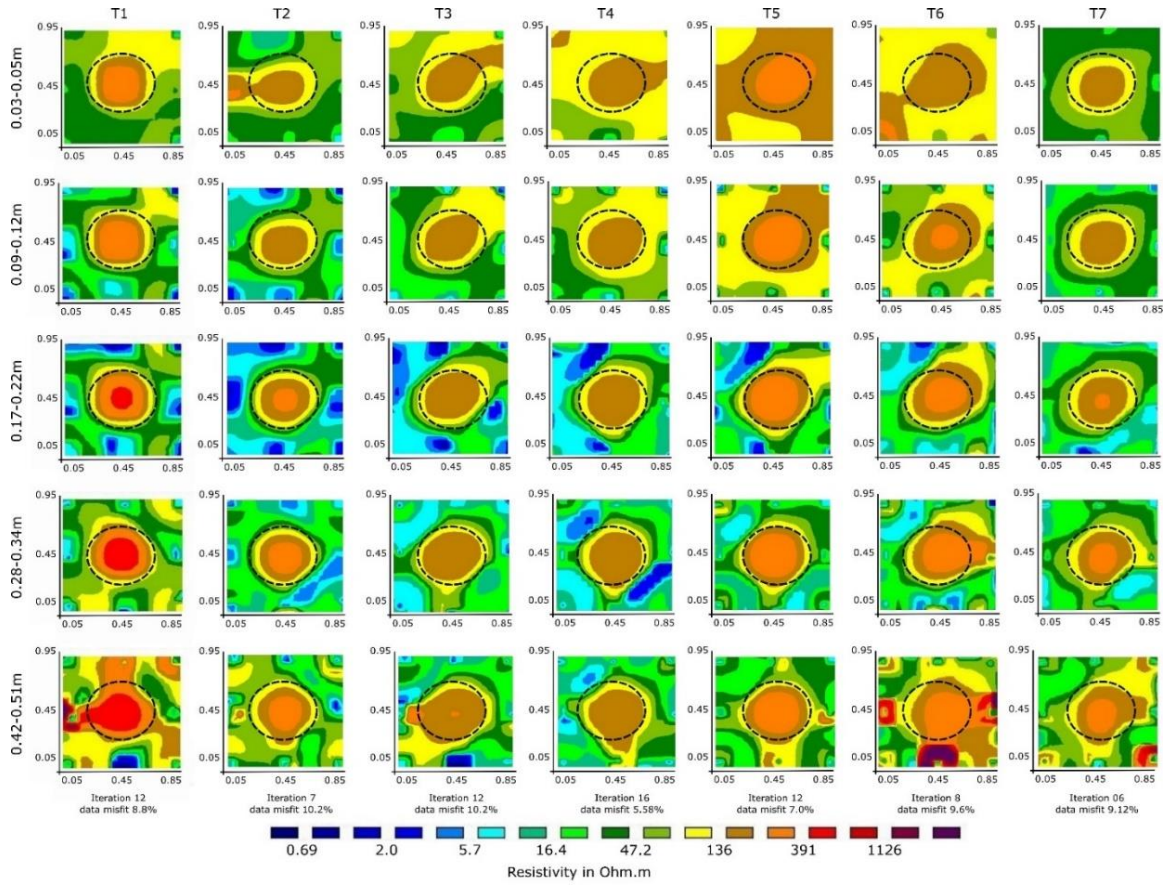


Figure 6. Cross-sectional XY slices obtained from the electrical resistivity imaging from the 3D processing capture the spatial and temporal variability of the root zoner's resistivity over different time periods (T1-T7).

Figure 7 presents the tomographic results from the 4D inversion of the acquired 3D DC data for almost 7 months, as depth slices for 5 different depths, 3-5 cm, 9-12 cm, 17-22 cm, 28-34 cm, and 42-51 cm. The individual 3D apparent-resistivity data models were filtered and then homogenized using some criteria as mentioned above for the 4D inversion. A total of 9,012 data points (quadripoles, Table 2) from each time-lapse 3D model were used to perform the 4D inversion and to build a 3D model of the subsurface with time (monitoring), for the tank. The inversion models demonstrate a satisfactory fitting with the measured data since the root mean square (RMS) error is 15.5% after 5 iterations. It must be mentioned that the RMS in 4D inversion is higher, but this can be

explained by the fact that one more parameter (the time) was incorporated into the inversion, and more data were removed from the datasets till all individual 3D datasets fulfill the criteria to perform 4D inversion and have the same number of points. This produces a “stiffness” to the model, and thus, the final RMS for the 4D model after inversion was higher than the average RMS of the 3D models after performing the inversion. The dashed line presents the expected spatial distribution of the root zone.

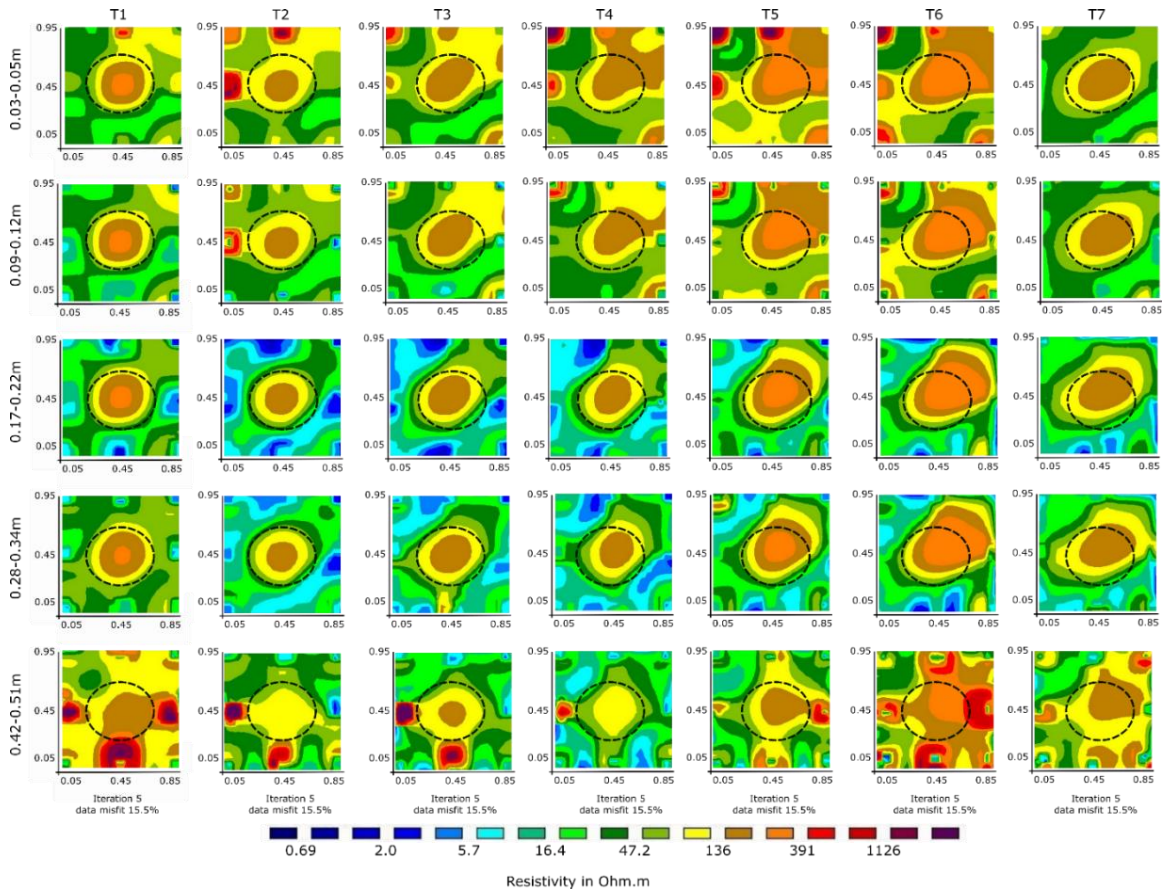


Figure 7. Cross-sectional XY slices obtained from the electrical resistivity imaging from the 4D processing, capturing the spatial and temporal variability on the root zoner’s resistivity over different time periods (T1-T7).

Figure 8 shows the temporal percentage change in resistivity with depth from the second measuring period in April 2023 (T2) till the end of the experiment in September 2023 (T7).

The percentage change was varied from -180 – 180%. The location of all the boreholes is

also shown as black circles. Anomalies around the boreholes' are expected due to the borehole's effects (difference in fluids resistivity within the borehole and the host materials and the effect of borehole's diameter), even though respective corrections had already been applied. The tomographic images resulted from the time-lapse inversion of the acquired resistivity data. The dashed line represents the expected spatial distribution of the root zone.

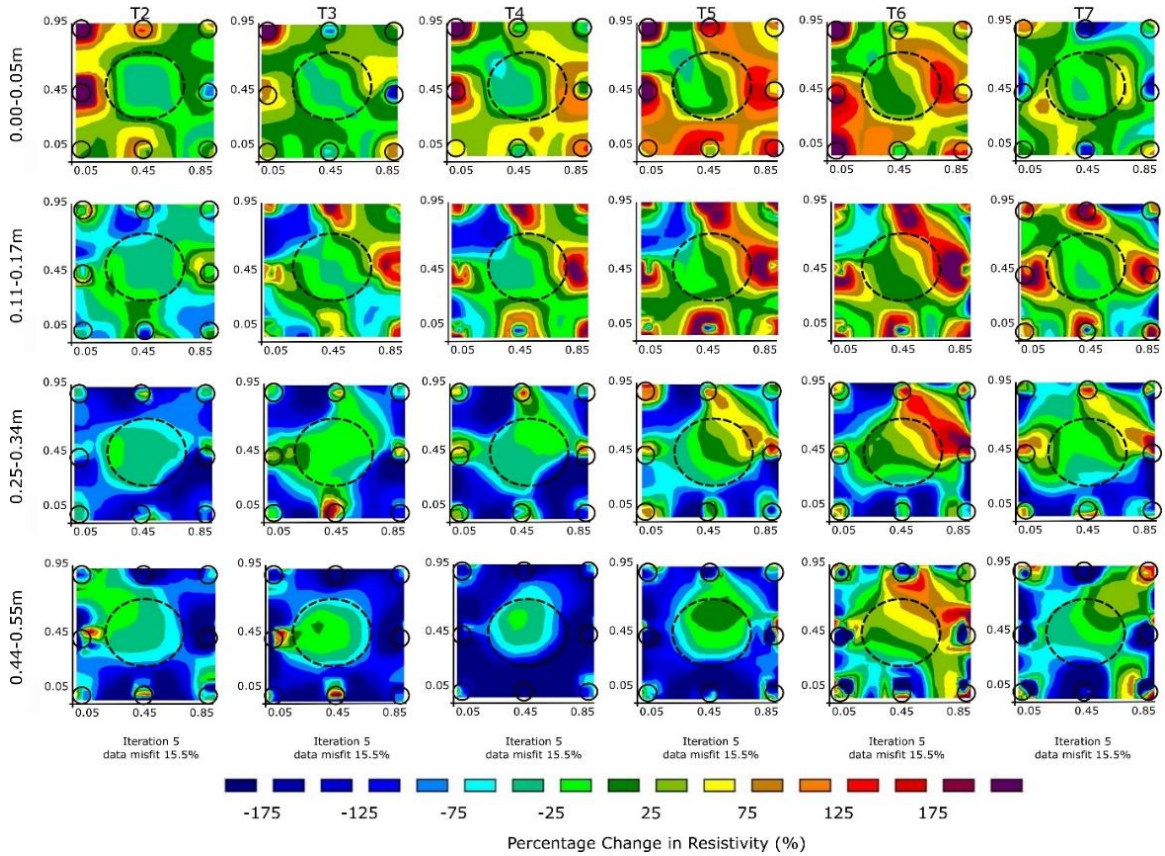


Figure 8. Temporal (from April – September 2023, T2 – T7, respectively) percentage change in resistivity. Black circles indicate the location of the boreholes and the dashed line in the center of the model represents the expected spatial distribution of the root

4.2. Detection of Resistive Zone

All resulting tomographic images from the 3D inversion (Figure 6) for all measuring periods and depths below 3 cm, clearly indicate a resistive zone depicted by a dashed circle in the middle of the study area. The anomaly is extended to a depth of 50 cm below the

surface. The main contradiction comes from the fact that the root zone is expected to be conductive and not resistive due to acidic characteristics, ions, and water surrounding the root zone. This is what has been observed in fine roots. Recent studies have demonstrated that the resistivity of stems can be reliably predicted based on their diameter and that this resistivity varies between different species and growth forms. More precisely, the resistivity of trees was approximately 200% greater than the resistivity of vines, and the resistivity of conifers was 135% higher than that of hardwoods. According to Attia al Hagrey (2007) woody root tissue generally exhibits greater resistivity than soft root tissue. Defandorf (1955) also found that leaves have a six times higher resistance than stems. Finally, in the case of full irrigation, the surrounding soil is more conductive than the root, and the current is expected to leave the root system near the stem–soil interface, as suggested by Urban et al. (2011) and Peruzzo et al. (2020). All the above indicate that several cases were reported where the root zone resistivity was higher than the surroundings. Additional subtle alterations were also detected both before and after the irrigation application within the topmost 5 cm between the measuring periods. The irrigation was consistently performed, but the water infiltration showed heterogeneity, as indicated by the lateral variations in resistivity.

The resulting 4D tomographic images for all measuring periods and depths below the surface (Figure 7) exhibit a resistive zone depicted by a dashed circle in the middle of the study area. The anomaly almost disappears after a depth of 50 cm below the surface. Specifically, from the top till the 4th depth slice, at a depth of 28-34 cm below the ground and for the first four measuring periods (March to June), the root zone is well defined as a high resistivity zone. As the temperature in Saudi Arabia increased to 48-50°C during July

(T5), the first 10cm of the soil was dried, and the root zone is shown only below the depth of 17-22 cm. Similar behavior was shown in August 2023 (T6) when the temperature was 43-45°C during the daytime, where the geophysical signature of the root zone was distorted till the depth of 34cm and disappeared in the last depth slice, 42-51cm below the ground. During September 2023 (T7), the root zone seems to have been partly recovered due to the sudden decrease of temperature, from 44°C to 38°C, producing more clear geophysical signatures for the first four depth slices, 0-34cm below the surface. It has to be mentioned that during the summer, June-August (T4-T6), the plant was watered daily with a higher amount of water, trying to keep the tree in good condition. The borehole effects in 4D inversion are clearer than the resulting tomographic images of the 3D inversion, most probably because of the lower number of data used or because the algorithm cannot apply the borehole effects correction in the 4D inversion. This is something that has to be exploited further. Finally, the tomographic 4D models show a clearer asymmetrical response from T3 till T7 since the rounded anomaly from the root zone shown in T1 and T2 has been replaced by a more elongated one probably indicating preferential flow paths during the watering after the T3 period.

The temporal percentage of change of resistivity (Figure 8) was used to show the effects of the watering and the plant growth, as well as the root zone. The changes mainly were visible in the center of the experimental site at X:0.45m and Y:0.45m, where the lemon tree was planted. Below the depth of 10cm, slight changes are observed in resistivity distribution and continue till the maximum depth of 55cm below the surface. The clearest tomographic images with the least resistivity changes were revealed at the area of the root zone (within the dashed circle) and at the depth slices of 0.25-0.34m and 0.44-0.55m,

especially at T2-T4, from April-June 2023. The images were totally distorted from July to September 2023 (T5-T7). It is worth mentioning that the resistivity change, especially in periods where good quality models were calculated, such as T2-T4, show a preferential flow (saturation) of the water along an NW-SE direction for T3 from the top till the depth of 17cm below the surface, and a NE-SW direction for T3 and T4 for the depth of 25-34cm indicating soil or root inhomogeneous characteristics, observed also in the 4D images. Findings about the root zone inhomogeneity can be used to design the proper irrigation by not necessarily surrounding the tree with water outputs but providing more water where the resistivity is lower based on the 3D/4D images.

All the above were confirmed by the ground-truthing of the controlled experiment. Specifically, after the end of the experiments, a small pit, as the best method for characterizing the root zone in soft soils, was opened close to the root and along one of the sides of the wooden box. The sandy soil was carefully removed in layers to expose the root distribution and to characterize the root geometry (extend) and location. As visual evidence, the main rooted area extended from the top (0 cm) to the maximum depth of 40 cm below the ground surface, and the occupied radius around the trunk was about 20 cm. Thus, the root zone covers an approximate volume of a sphere with a radius of 20 cm, which agrees with the resulting geophysical images (Figures 6 and 7, depicted by the dashed circle).

After successfully applying the ERI method to characterize the root zone of a lemon tree, several experiments should be followed. Geophysical methods (ERI and GPR) and sensors should be used jointly. The sensors can provide local real-time information about water saturation in different places. A few sensors cannot be used to replace the 9000 or 15000

points of acquired resistivity measurements representing the 3D/4D model of the root zone but can be used to calibrate the resistivity measurements and convert the 3D/4D resistivity model to 3D/4D soil moisture representation. Different water qualities can also be applied, tested, and evaluated by monitoring (expanding or shrinking) the root zone and the health condition of the tree (based on chlorophyll measurements). Finally, the resistivity or water saturation and moisture models can be used to apply proper numerical models such as, HYDRUS 1D/2D, to estimate the root water uptake (RWU). The RWU is a fundamental process that controls the water balance in the soil and plays a vital role in managing agrosystems. Finally, in such a controlled experiment, different soil types and land cover can be used to monitor the fluctuations in soil resistivity/moisture levels, which can vary greatly regarding their spatial and temporal variations.

CHAPTER 5

THREE-DIMENSIONAL IMAGING OF ROOT DISTRIBUTION OF AGRICULTURAL CROP USING GROUND PENETRATING RADAR

5.1 Root Zone Detection

This study aimed to cluster areas of fine root distribution rather than focus on individual traits by using a low-frequency GPR; hence, the expected hyperbolic pattern did not appear. Instead, the radargram depicted an inward concave pattern, which is interpreted as the area of a root system. This concave pattern is explained as the existence of the root system decreasing the GPR propagation velocity, which is shown as an increase in the two-way GPR travel time, i.e. concave pattern. Given that we already know the actual root system during tree plantation, it can be stated that the degree of the concave is directly proportional to the size of the root zone. Hence, the concave pattern is used as an indirect indication to the location and size of the root zone.

Under controlled and optimum conditions, the use of a 400 MHz antenna in this study achieved the desired depth of investigation. We were able to, successfully, determine the zone where fine roots were concentrated, irrespective of their orientation, size and individual roots interval, although individual fine roots could not be distinguished. While a higher frequency antenna such as the 2 GHz, may allow for the detection of individual fine roots (Molon et al., 2017), but its penetration depth would be limited to 20 cm (Barton & Montagu, 2004). Moreover, considering the natural characteristics of fine roots that are entangled with each other in the soil, the interpretation of waveforms on radargram would

be difficult. Thus, we suggest that a higher frequency is unlikely to provide helpful information for fine roots detection.

Based on 71 GPR profiles collected during acquisition, differences in the radargram were apparent between the area with and without root system. In the first profile, which is located at the bottom of the box, no reflected wave was observed (Figure 9). The root system was first detected in the GPR profile 49 recorded at a depth of 31.5 cm from the top of the box, and the subsequent profiles (depth < 31.5 cm from the top of the box) showed the presence of the root system all the way to the top of the box, with small amplitude reflected waves visible in each of these profiles (Figure 10). Overall, the reflected waves due to root system were observed in the radargram in the depth range 0-31.5 cm from the top of the soil box, represented by profile 49 to 71. The amplitude increased as it approached the surface, indicating that fine root distribution is mainly concentrated in the upper soil profile, consistent with the distribution of the fine roots inside the box.

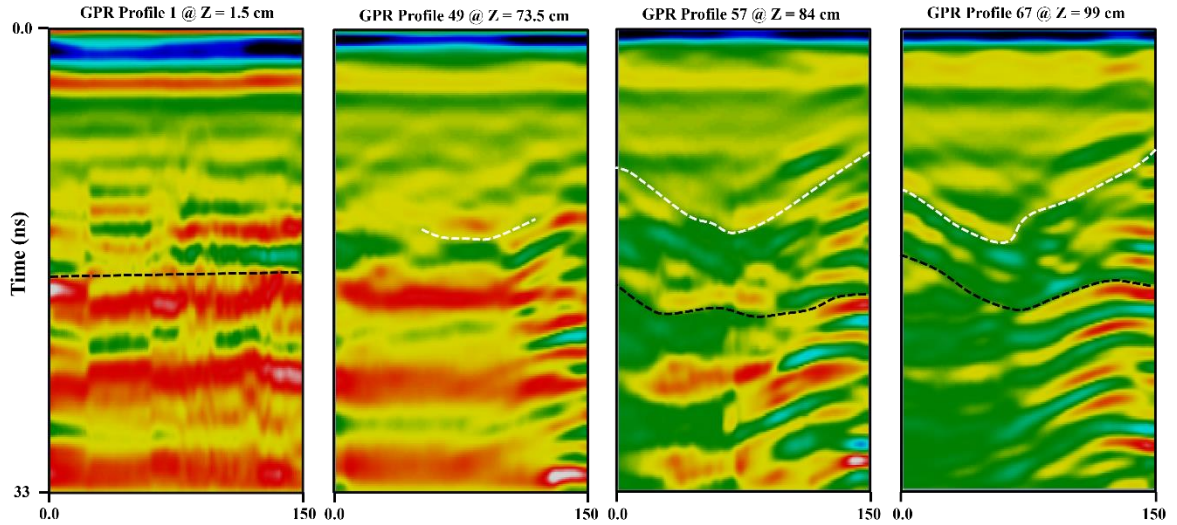


Figure 9. Horizontal slices at different depth indicate the presence of root system. Profile 1 is located at the bottom box, while the last profile (profile 71) is located at the top of soil box. The detected root system is marked by a white line. The black line indicated reflection from the back of the wooden box. Profile 1-48 represents the area without root system, while profile 49-71 reflects the area with the existence of root system.

While the optimal conditions for root detection of a particular tree and site yet to be determined, GPR tends to yield better results in sandy soil under dry conditions (Guo et al., 2013; Molon et al., 2017; Nichols et al., 2017). Water content of the soil is one of the factors that could affect root detections, as it might interfere with a signal transmission of GPR and generate a difficult-to-interpret profile (Rodríguez-Robles et al., 2017). This is apparent in this study, where differences between pre-watering and post-watering conditions were observed. The radargram under dry condition (Figure 10a) at each horizontal slice showed stronger reflection than the wet condition (Figure 10b). This study confirms that even though water content could affect the GPR performance on roots' mapping, the presence of roots was still detectable.

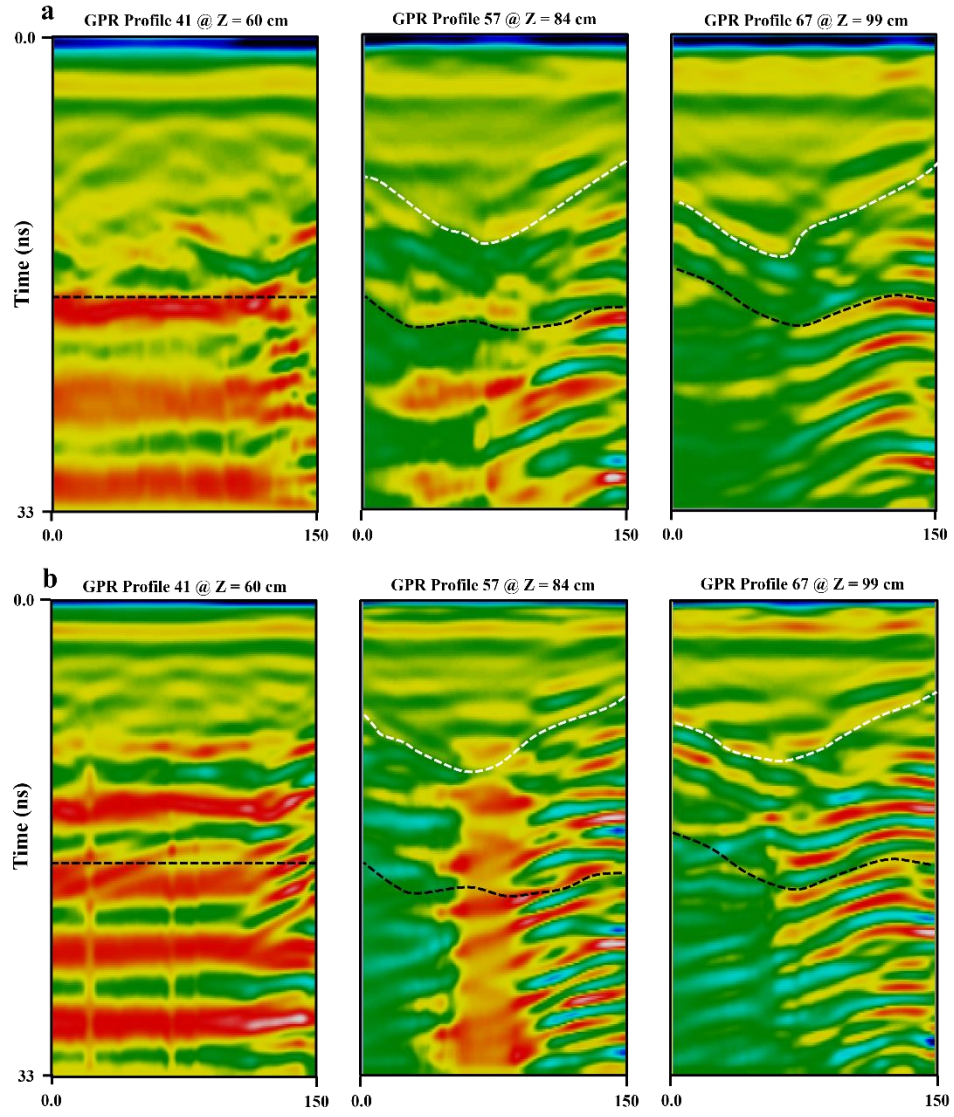


Figure 10. Horizontal slice at different depths under (a) pre-watering and (b) post-watering conditions. The detected root system is marked by a white line. The black line indicated reflection from the back of the wooden box.

5.2 Three-Dimensional Visualization of Root Zone

The recorded GPR profiles under pre-watering conditions were utilized to reconstruct the 3D visualization of the distribution of the fine roots. This reconstruction aims to enhance

the interpretation of both vertical and horizontal root systems distribution, providing valuable insights for the implementation of irrigation strategies. In this study, the majority of fine roots were concentrated in the upper 0-28 cm of the soil profile, with a significant change of fine roots distribution observed in the deeper soil profile (28-31.5 cm) (Figure 11a). Generally, their concentration decreased with increasing soil depth. Figure 11b,c illustrates the lateral distribution of the area where fine roots were accumulated, indicating a horizontal orientation in all directions. In particular, the distribution of fine root system tended toward the southeast.

Since root concentration typically correlates with resources availability, the observed spatial distribution of fine roots in this study is likely influenced by the type of irrigation used in this experiment (flood irrigation). In flood irrigation, roots tend to be more concentrated in the upper soil layer compared to non-flooded irrigation treatment (Bian et al., 2023; He et al., 2013). This condition might represent how crops adapt to environmental change. Irrigation water from flood irrigation tends to be more abundant horizontally in the upper soil profile, hence the expected root system would be shallower and spread wide.

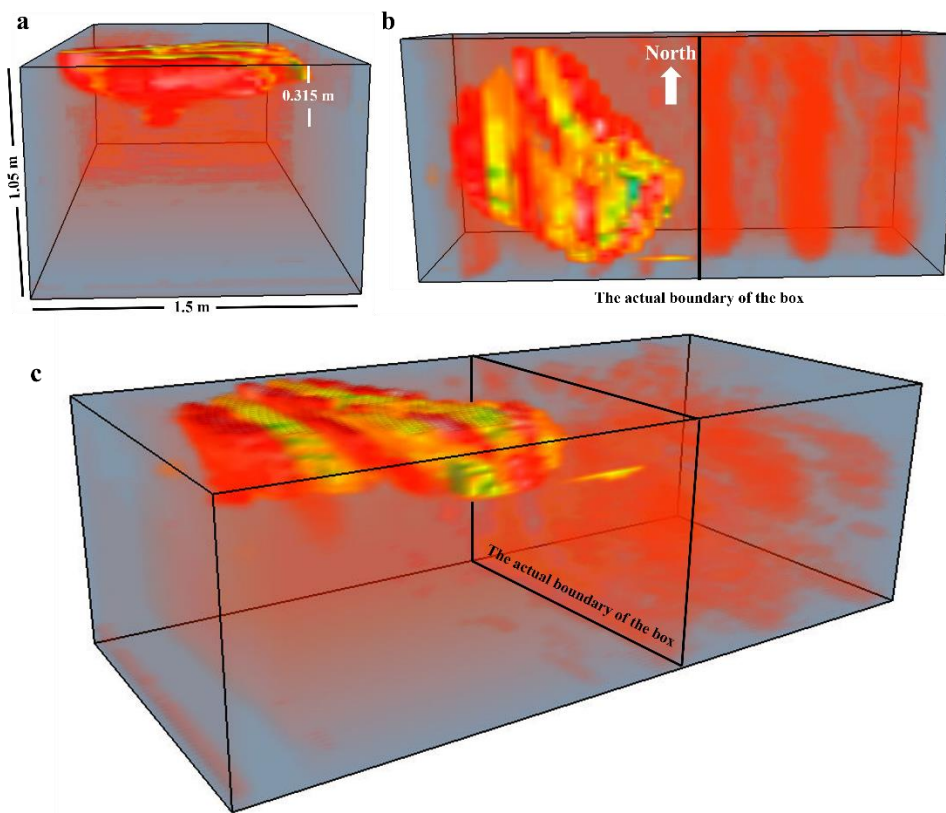


Figure 11. Visualization of three-dimensional fine root distribution at (a) front view (b) top view and (c) 3D view

CHAPTER 6

SIMULATING TREE ROOT WATER UPTAKE IN THE FRAME OF SUSTAINABLE AGRICULTURE FOR EXTREME HYPER-ARID ENVIRONMENTS USING MODELING AND GEOPHYSICAL TECHNIQUES

After irrigation, the soil moisture profile (SMP) needs to be defined as the initial condition. The SMP is indirectly calculated using the non-destructive ERT method. The way that ERT was used to calculate a detailed and accurate SMP is going to be de-scribed in the following section. The simulation of RWU was conducted at an hourly time step. In addition, to reflect the diurnal variation, the simulation was designed at 08.00, 11.00, 14.00, 17.00 and 22.00.

6.1. Soil Moisture Profile Derived from ERT

Figure 11 displays the final 3D ERT processed models after 7 iterations and a final root-mean-square (RMS) of 10.2%. This 3D resistivity model is one of the total seven time-lapse tomographic models performed during this research. The colors represent the spatial resistivity (soil moisture) distribution in 5 depth slices: 3-5cm, 9-12cm, 17-22cm, 28-34cm, and 42-51cm. Hot (red) colors indicate high resistivity areas and cold (blue) colors identify low resistivity anomalies. These depth images show the volume of the root system/zone, as depicted by the dashed circle, as a high resistivity anomaly due to the complexity of the root zone compared to the homogeneous (low resistivity) host soil. The most evident (least RMS) tomographic detection of the root zone is shown at the 4th depth slice (28-34cm),

which agrees with the expected depth where the colonized root zone is expected to be found (Y. Liu et al., 2022a; Yu et al., 2007).

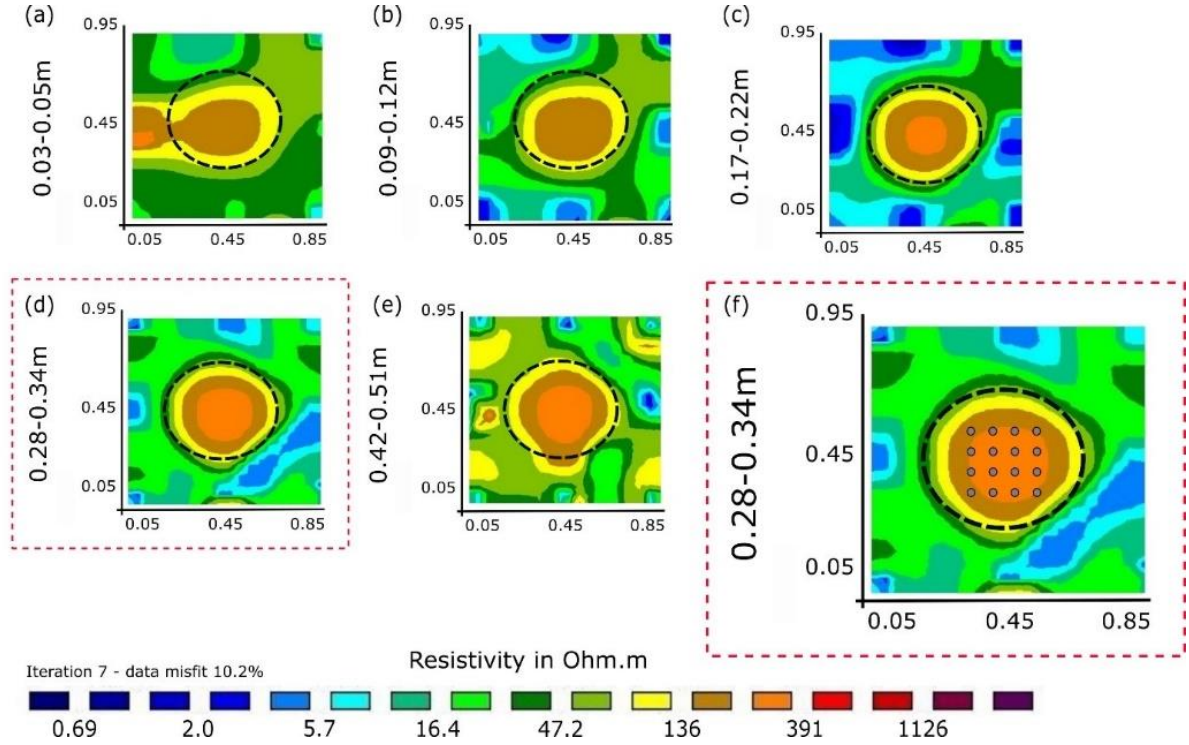


Figure 12. Depth slices of electrical resistivity tomography after seven iterations at different depths: (a) 3-5 cm, (b) 9-12 cm, (c) 17-22 cm, (d) 28-34 cm, and (e) 42-51 cm. (f) The depth slice where the most evident tomographic detection of the root zone (least RMS) was observed. Color indicates spatial resistivity distribution (soil moisture) within soil.

The 3D resistivity model for each of the seven time-lapse periods (from March to August 2023) has a spatial resolution of 5cm (corresponding to the electrode spacing used) and a vertical resolution of 3-7cm, depending on the depth. To obtain a representative and accurate soil moisture profile based on multiple resistivity measurements, a grid of 16 nodes (represented by grey dots in Figure 12f) was used to sample the root zone. The average resistivity from these 16 sampling points was calculated for 15 depths, ranging

from the surface to a maximum depth of 110 cm, and provides a comprehensive characterization of soil moisture dynamics (Figure 13).

Based on the vertical distribution of the resistivity during the experimental period, the maximum resistivity is depicted at a depth of 38cm (yellow-shaded cells in Figure 13), which agrees with the literature (Y. Liu et al., 2022b; Yu et al., 2007). The parabolic shape of the resistivity distribution with depth is consistent with the study by Mishra et al (2015) since the measurements were always acquired in a short time after the irrigation to ensure good contact resistance and the collection of high-quality resistivity data.

Since soil moisture profiles are required as input data for estimating RWU using HYDRUS 1D, attempts were made to convert the final vertical resistivity distribution into water content or soil moisture. The average resistivity profile (Figure 13) ranges from 75 to 304 Ohm. Given the expected soil moisture content in sandy soils ranging from 5% to 12%, the soil moisture profile derived from the resistivity distribution was estimated and graphically presented.

Depth (m)	Av. Res.	Moist. (%)
-0.01	210.30	9.10
-0.04	214.43	9.20
-0.07	222.44	9.40
-0.11	234.23	9.78
-0.15	249.38	10.30
-0.19	266.52	10.90
-0.25	283.10	11.20
-0.31	296.27	11.65
-0.38	303.66	12.00
-0.46	302.98	11.80
-0.56	291.50	11.50
-0.67	264.78	10.70
-0.79	220.93	9.30
-0.94	157.13	7.50
-1.10	74.85	5.00
min RES	74.85	5
max RES	303.66	12
aver. RES	239.50	

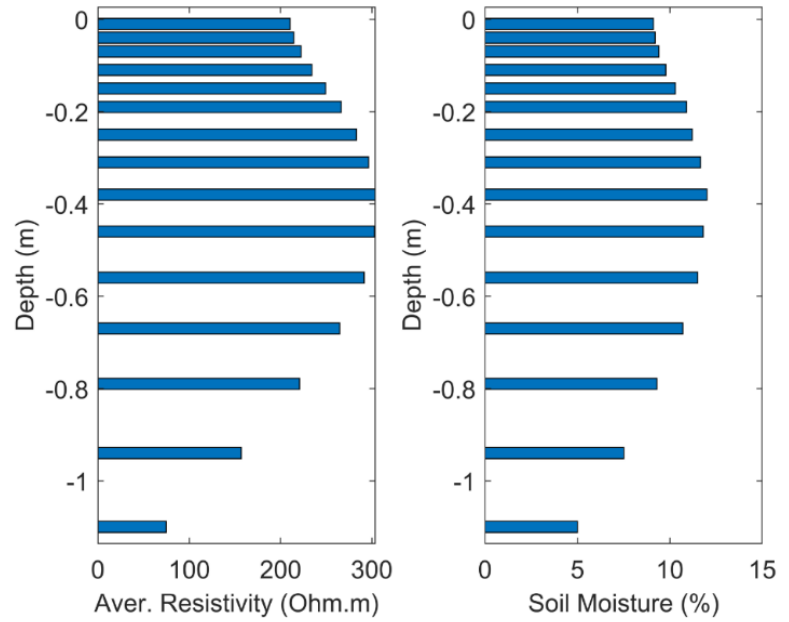


Figure 13. The average resistivity and soil moisture profile from all measuring periods derived from ERT. The yellow-shaded cells also depict the highest resistivity and soil moisture, showing the center of the root zone.

6.2. Model Calibration

Considering the results of soil mechanical composition, soil hydraulic characteristics were estimated through the ROSETTA neural network prediction model and hydraulic conductivity test. In turn, the estimated values of soil hydraulic properties were calibrated using the time-varying soil moisture profile values provided by the aforementioned ERT geophysical technique. During the calibration process the good agreement between soil moisture profile values provided by the ERT method and the HYDRUS 1D simulation results was demonstrated based on root mean square error (RMSE) and correlation coefficient (R) statistical indices, indicating a successful calibration process (Figure 14).

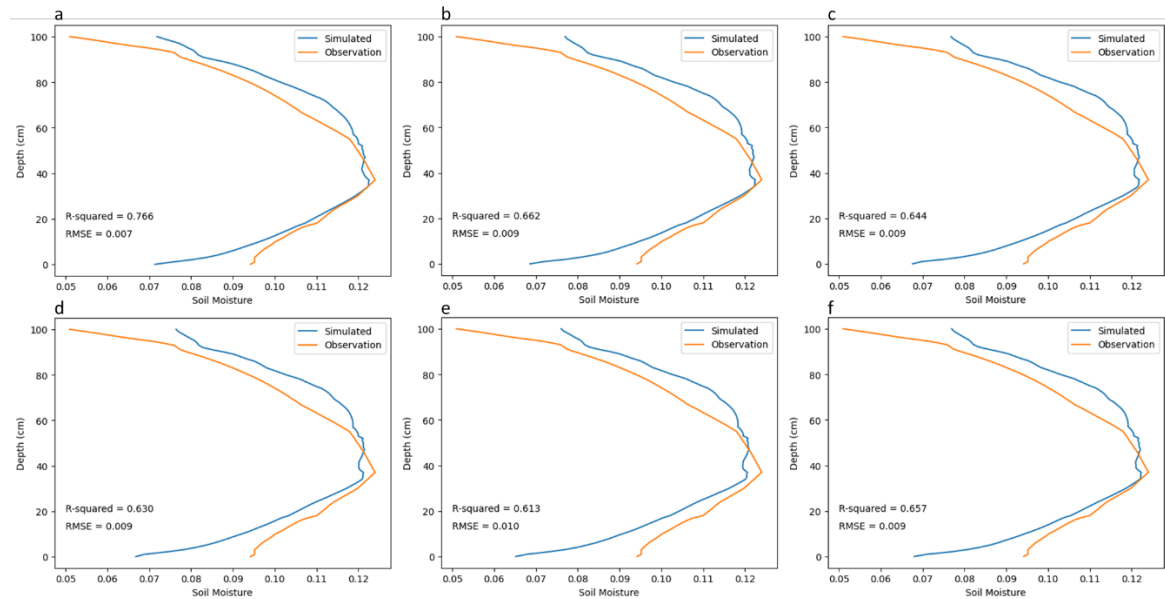


Figure 14. HYDRUS 1D calibration results for each month: (a) March, (b) April, (c) May, (d) June, (e) July, and (f) August. Good agreements between calibrated model with observed soil moisture were observed.

6.3. Simulated Soil Water Content

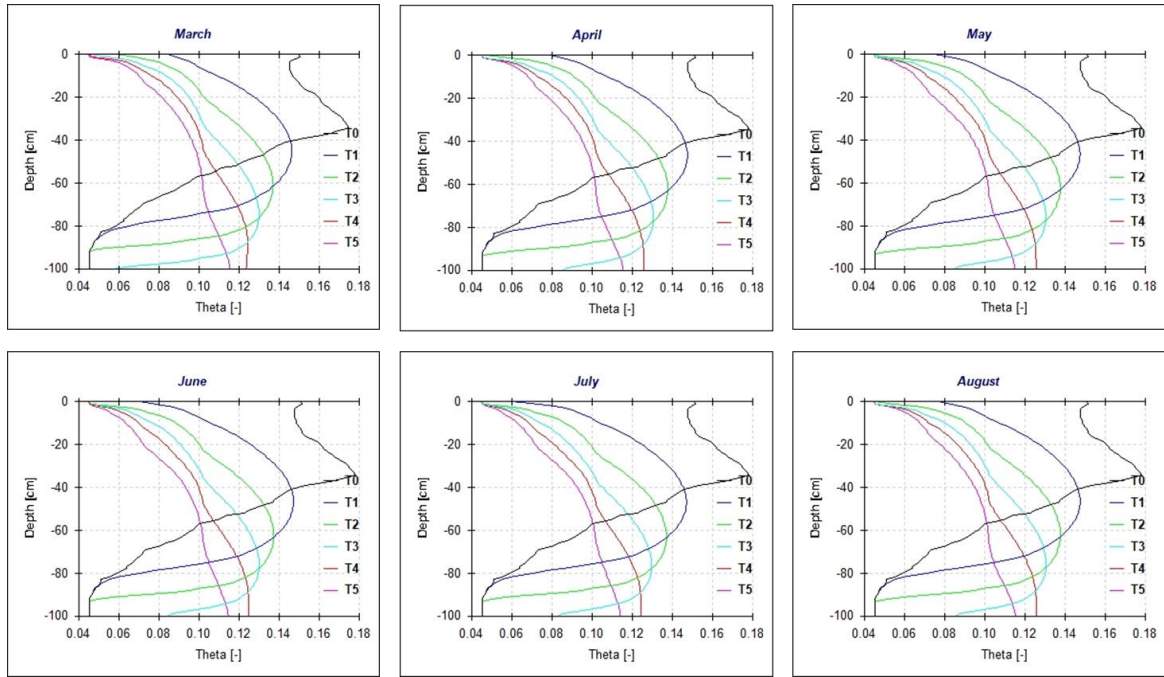


Figure 15. Simulated soil water content on March 23, April 11, May 14, June 1, July 11, and August 21, 2013. T0 is the initial condition, while T1, T2, T3, T4, and T5 represent the time intervals at 08:00, 11:00, 14:00, 17:00 and 22:00, respectively.

The calibrated model was employed to simulate soil water content at a depth of 0-100 cm on an hourly time step for each month (Figure 15). As evident from the simulated soil water content, overall, the soil water content profile exhibited similar patterns with little change over different periods. There is a general trend of decreasing total soil water content over time due to soil water consumption and redistribution. A notable pattern emerges during the initial hours following irrigation when the highest soil water content for each period is consistently observed at a depth of 80-90 cm, before rapidly decreasing, showing the parabolic pattern. Over the following hours, the soil water content profile for each period changed its typical vertical pattern, with water content gradually increasing with depth and

the highest soil water content was predominantly located at depths of 80-100 cm. Overall, the moisture content at a depth of 0-30 was significantly lower than the soil profile during the different periods.

6.4. Diurnal and Seasonal Variations of RWU

The diurnal dynamics of RWU simulated by HYDRUS 1D from March to August 2023 are illustrated in Figure 16a. The simulated RWU for each month exhibited fluctuations with typical peaks during the morning period from 08.00 to 11.00. Specifically, RWU increased during the first several hours of sunlight, reaching a maximum before midday, and then decreased until the end of the observation period (22:00). This diurnal variation might indicate that the morning period can be considered as the best irrigation timing when RWU is the highest. At the seasonal time scale, the hourly RWU values were generally larger in July, resulting in larger cumulative RWU values, as shown in Figure 16b, while the most negligible RWU variation was observed in March. RWU values started to increase in March, reaching their peaks in July before and decreasing again until August.

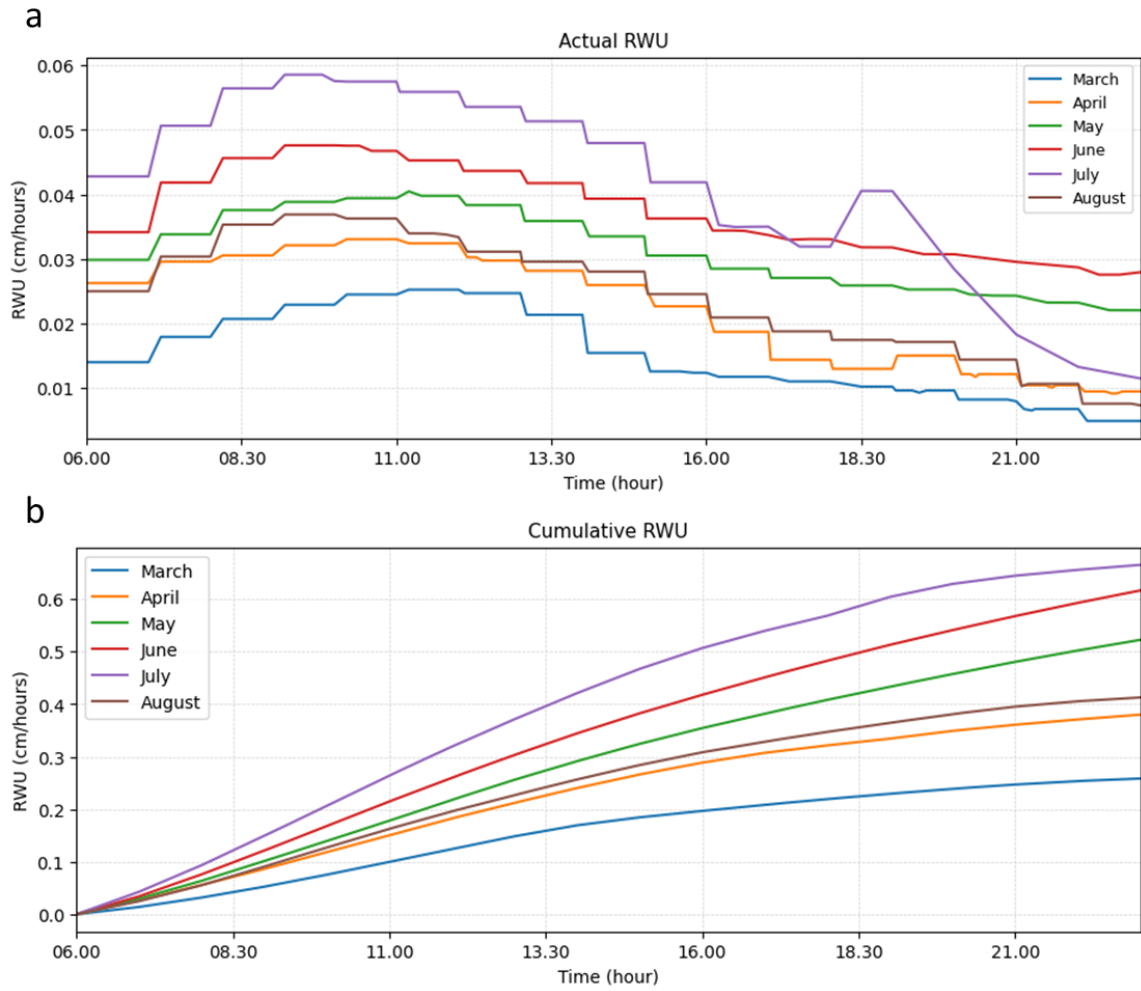


Figure 16. (a) The changes of RWU rates and (b) cumulative RWU in different months. The simulation period spans from 06:00 in the morning to 22:00 at night.

6.5. RWU at Different Soil Depths

The RWU rate based on the Feddes model is depicted across different depths and times, providing insights into the temporal and spatial patterns of water extraction by plant roots (Figure 17). Overall, RWU primarily occurred in the upper 30 cm layer of the soil profile, reflecting the actual concentration of roots in this area. This also explains why the lowest soil water content was always observed at the upper soil profile (depth of 0-30 cm) than

the rest of soil layer (depth of 30-100 cm). Following irrigation, the RWU zone remained within the depth of 0-30 cm during the initial hours. However, as time and temperature increased, the RWU zone gradually shifted from the upper to the lower soil profile. The most significant shift of the RWU zone occurred during the summer periods. In June and July, higher RWU rates were predominantly distributed at depths of 4-30 cm and 7-30 cm beneath the soil surface, suggesting an increase in soil evaporation during mid-day. Therefore, managing irrigation water during the summer months in accordance with RWU zone is essential to avoid water loss through evaporation.

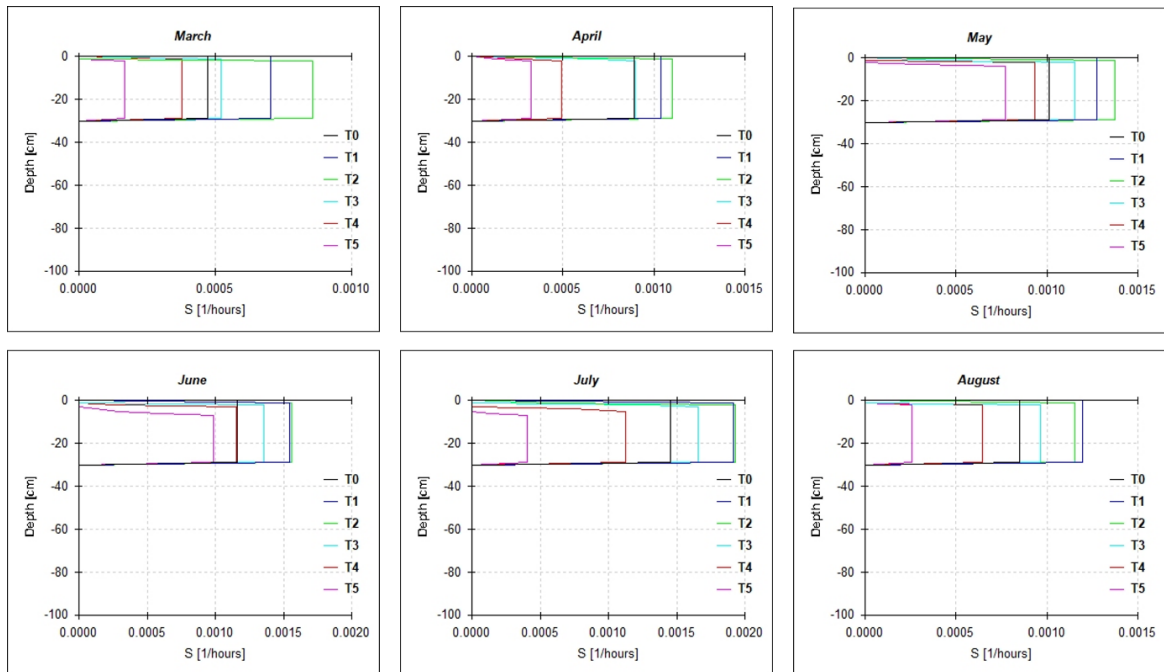


Figure 17. RWU rates at various soil depths and time periods. The designation 'T0' represents the initial condition, while 'T1' through 'T5' correspond to time intervals at 08:00, 11:00, 14:00, 17:00, and 22:00, respectively.

CHAPTER 7

SIMULATION OF SOIL WATER BALANCE AND IRRIGATION SCENARIOS IN FLOOD-IRRIGATED LEMON PLANTATION IN ARID ENVIRONMENT

7.1. Model Performance

HYDRUS-1D was further calibrated by the measured ERT-derived soil water content collected during the study period. Prior to model calibration, soil hydraulic parameters required in the model were obtained through laboratory assessment and neural network prediction embedded in HYDRUS-1D package. The soil's physical properties at the depth of 0-100 cm were determined to be uniform since there was no significant stratification difference within the vertical soil profile.

The comparison between simulated soil water content and observed ERT-derived soil moisture for the depth of 0-20 cm, 20-40 cm, 40-60 cm, 60-80 cm, and 80-100 cm is illustrated by figure 18. The root mean square error (RMSE) and mean absolute error (MAE) were selected to assess the model's performance. The better the simulated model, the closer the error to zero. During the calibration period, the RMSE ranged from 0.002 to 0.016 and MAE ranged from 0.001 to 0.007, indicating good agreements between simulated and observed soil water content. The higher accuracy is also visible during the validation period, where the value of both RMSE and RAE ranged from 0.003 to 0.02.

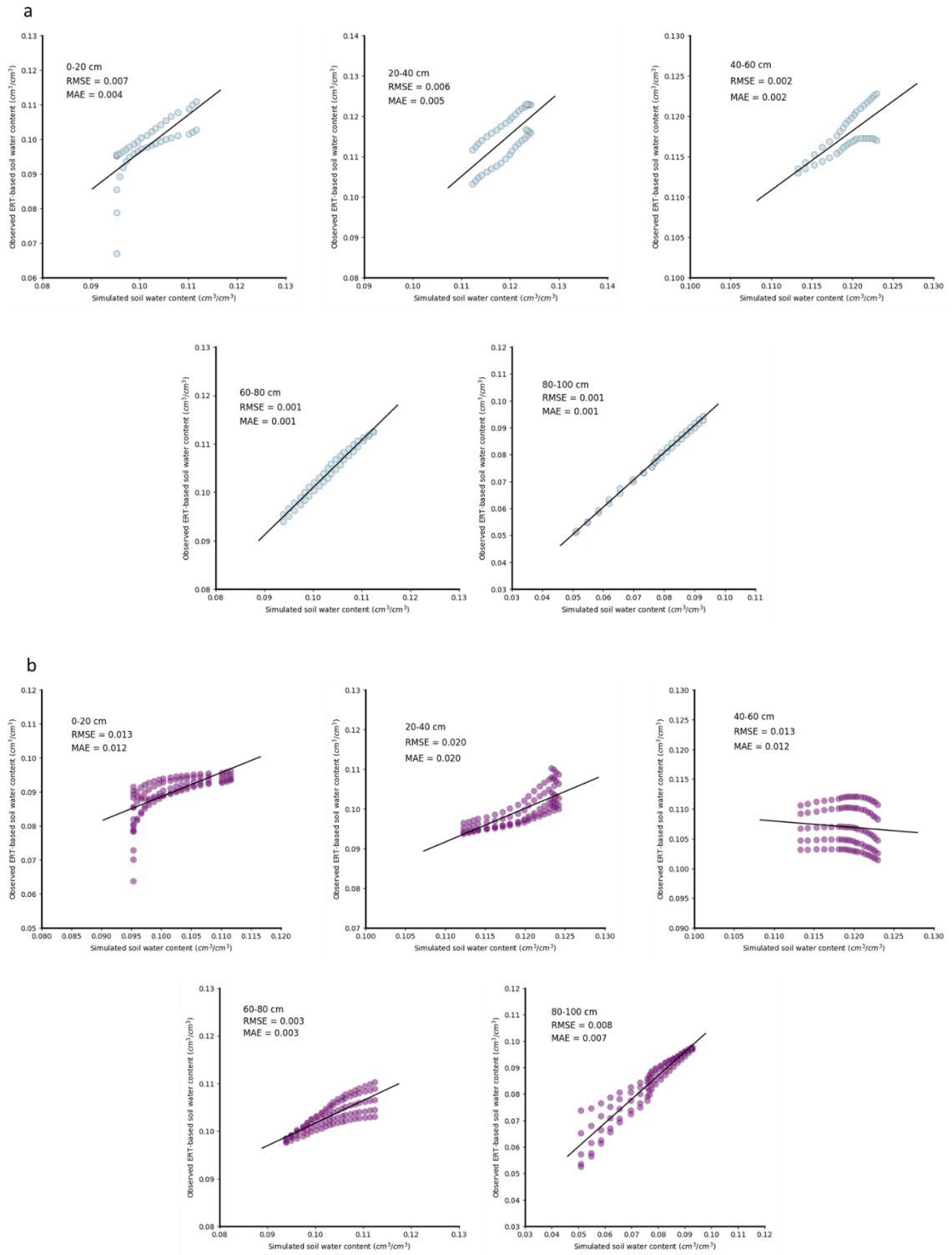


Figure 18. Comparison of observed and simulated soil moisture at different depth during the study period for (a) calibration and (b) validation processes

The highest discrepancies between simulated and observed values were found within the 20-40 cm soil layer. In general, the shallower soil layers have higher RMSE and MAE compared to deeper soil layers. This might be attributed to the effect of irrigation where water tends to infiltrate preferentially and quickly into deeper soil layers due to large pore spaces formed by the presence of root system (Y. Wang et al., 2024), which is in this case was distributed within 0-40 cm below soil surface. Subsequently, this process leads to an increase in soil water content, resulting in higher RMSE and MAE, which is agreed with the soil content profile of each month (figure 19). On the other hand, the deeper soil layer has much lower soil water content, thus RMSE and MAE were smaller, resulting in higher accuracy during calibration and validation processes.

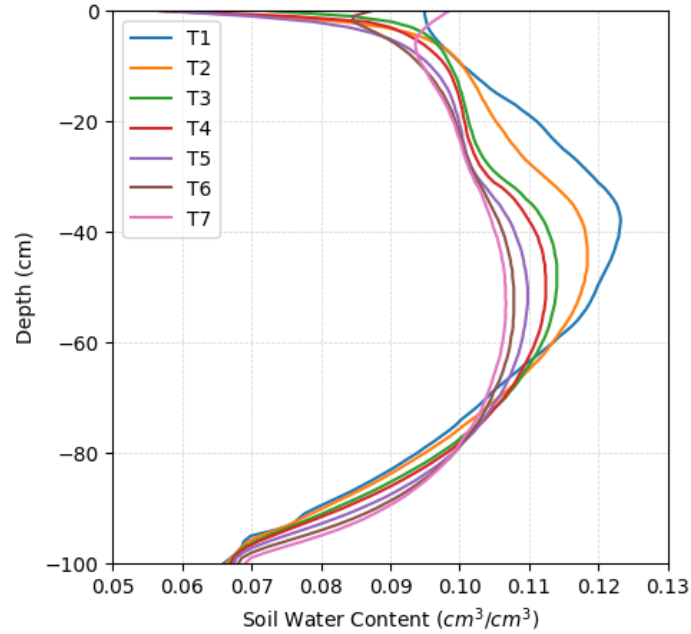


Figure 19. Soil water content profile at different periods. T1, T2, T3, T4, T5, T6 and T7 represent March, April, May, June, July, August, and September 2023, respectively.

7.2. Soil Water Flux under Different Irrigation Simulation

After calibrating the model, HYDRUS-1D was used to simulate different irrigation scenarios formulated by CROPWAT. The output of this model is soil water fluxes, such as transpiration, evaporation, and deep percolation. During the experiment period, no rainfall was observed and there was no excess water left at the experimental site, hence surface runoff was not involved in this study. The workflow of methodology adopted in this study is depicted by figure 20.

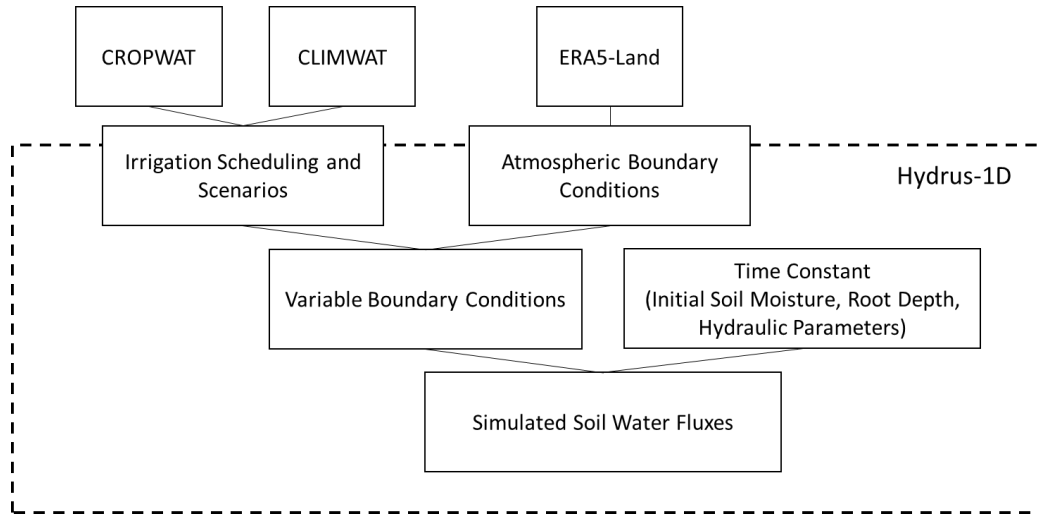


Figure 20. The workflow of the method to generate soil water fluxes under different irrigation scenarios by utilizing CROPWAT, CLIMWAT, and Hydrus-1D

7.2.1. Transpiration and Evaporation

The simulation of plant transpiration and evaporation under different irrigation scenarios is depicted in figure 21. As can be seen, water stress occurred in all irrigation scenarios, indicated by the difference between potential cumulative transpiration and actual cumulative transpiration (figure 21a). The main factor attributed to water stress was that the scheduled irrigation water amount, estimated by multiplying the crop coefficient with reference evapotranspiration through CROPWAT-CLIMWAT, underestimated the actual crop water requirements (figure 22). The latter parameter was calculated based on ERA5-Land meteorological parameters for a 7-months experiment (March to September 2023).

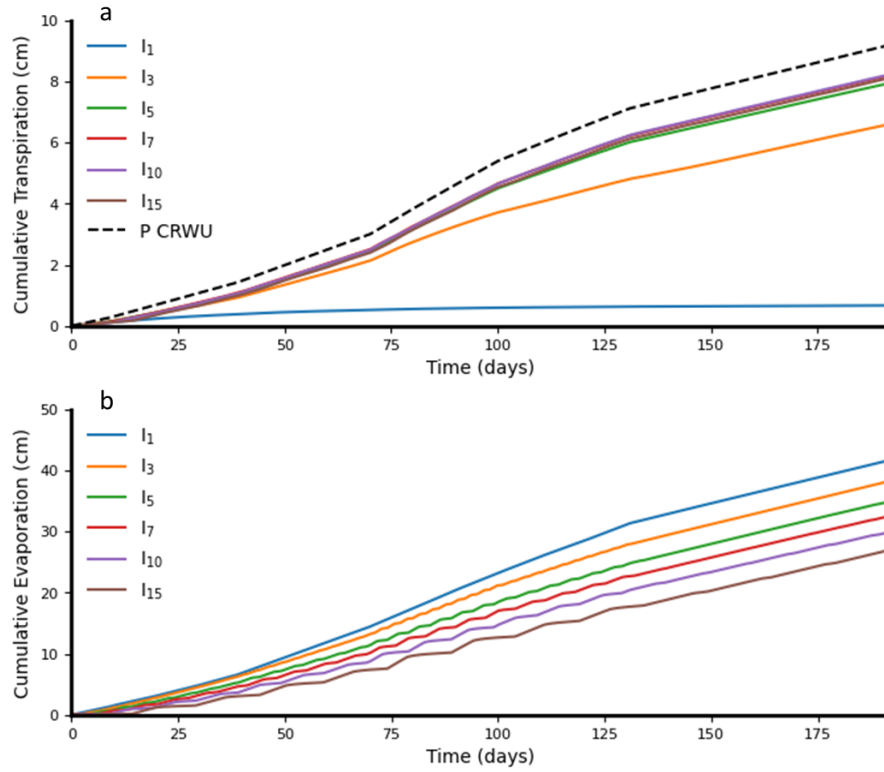


Figure 21. (a) cumulative transpiration and (b) cumulative evaporation simulated by HYDRUS-1D. The dashed black line represents potential cumulative transpiration.

As depicted by figure 21a, the most significant water stress was observed under the existing irrigation (I₁). As the irrigation interval increased, transpiration also increased, resulting in a decrease in water stress before increasing again during I₁₅. The total amount of water stress during the study period under I₁, I₃, I₅, I₇, I₁₀ and I₁₅ was 87.52 mm, 25.94 mm, 12.48 mm, 9.9 mm, 9.6 mm, and 10.8 mm respectively. Further, increasing the irrigation interval could also lead to a reduction in evaporation, as observed from figure 21b. Under the same evaporative demand, the lowest soil evaporation was observed under I₁₅, followed by I₁₀, I₇, I₅, I₃ and I₁.

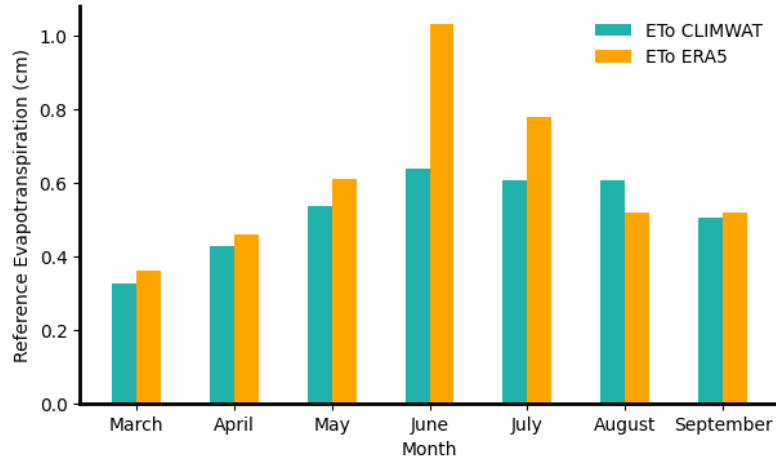


Figure 22. The comparison between ETo estimated by CLIMWAT and ETo calculated based on ERA5-Land meteorological parameters. It shows that CLIMWAT underestimated the actual Eto, thereby the scheduled irrigation cannot fulfill the actual crop water requirement.

7.2.2. Deep Percolation

Larger deep percolation of soil water in which the water moves downward into groundwater might indicate less effective irrigation. This process is primary influenced by the soil permeability coefficient and irrigation intensity. Cumulative deep percolation for each scenario simulated by HYDRUS-1D is depicted in figure 23. In this study, 100 cm is defined as the boundary for deep percolation. Therefore, deep percolation was defined when water passed downward out of the 100 cm soil column. As shown, the lowest percolation occurred under the existing irrigation practice (I_1). The deep percolation dramatically increased when larger irrigation interval and greater irrigation water amount were adopted. This phenomenon is notable in soil with high hydraulic conductivity (H. Wang et al., 2010) as demonstrated in this study. In this study, the highest water loss through deep percolation was observed under the I_{15} scenarios.

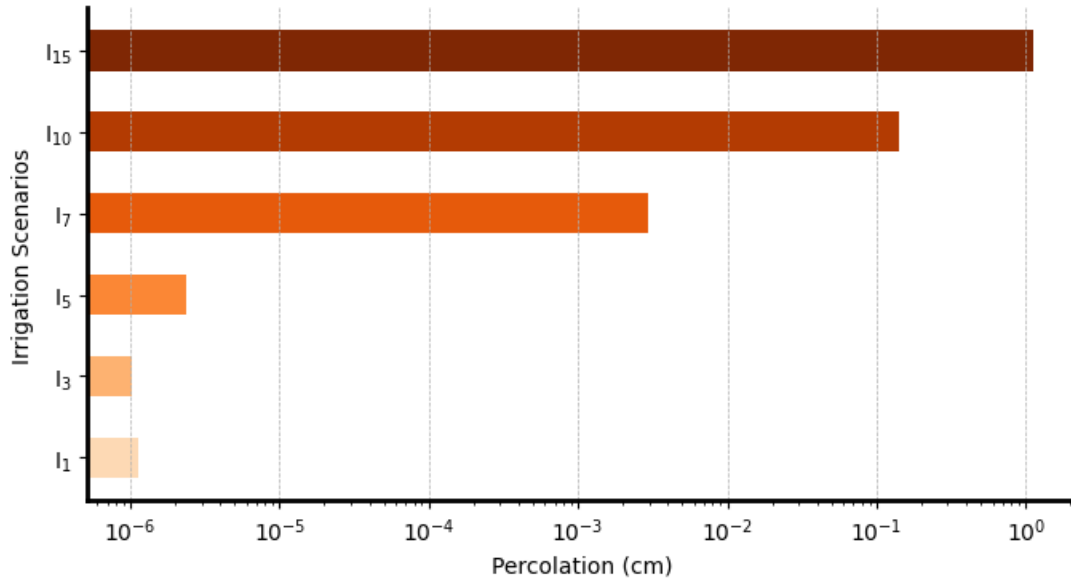


Figure 23. Cumulative deep percolation of each irrigation scenario. The x axis was set as log scale.

7.2.3. Water Components

Among the water components, soil evaporation has the highest relative contribution to soil water loss under all different irrigation scenarios, followed by transpiration and deep percolation (Figure 24). In fact, this pattern represents the typical soil water loss in arid environment (Alazard et al., 2015; Chen et al., 2024). As seen, with increasing irrigation interval or lower irrigation frequency, soil evaporation decreased, crop transpiration increased, and deep percolation increased. However, compared to other soil water fluxes components, the amount of deep percolation in all irrigation simulations was much lower.

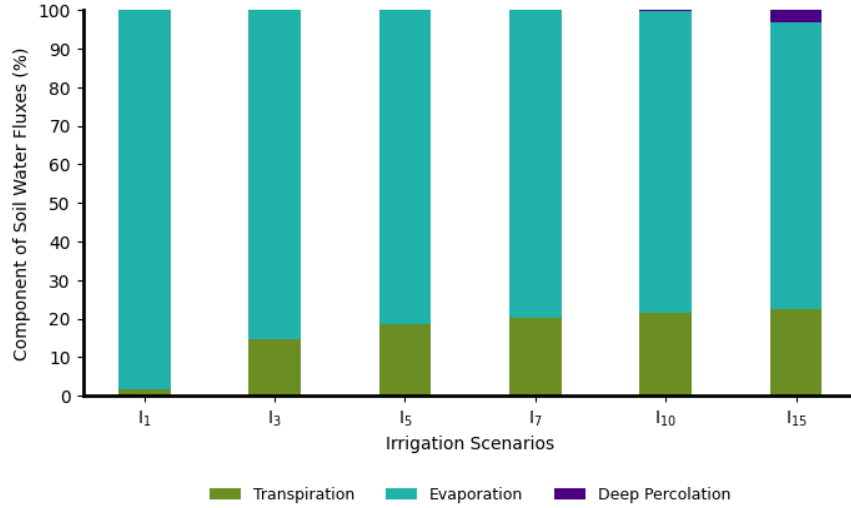


Figure 24. Comparison of soil water fluxes components under different irrigation scenarios

7.3. Irrigation Efficiency

According to simulation, increasing irrigation interval would enhance transpiration and reduce soil evaporation, yet the deep percolation would increase exponentially with a reduction in irrigation frequency. In order to select the optimum irrigation scenario, the ratio of T_a/T_p was used as a threshold. Figure 25 illustrates the value of T_a/T_p under different irrigation scenarios, showing that the highest T_a/T_p was observed during I_{10} . As irrigation frequency decreased, the value of T_a/T_p increased gradually, reaching its peak at the I_{10} scenarios before decreasing again.

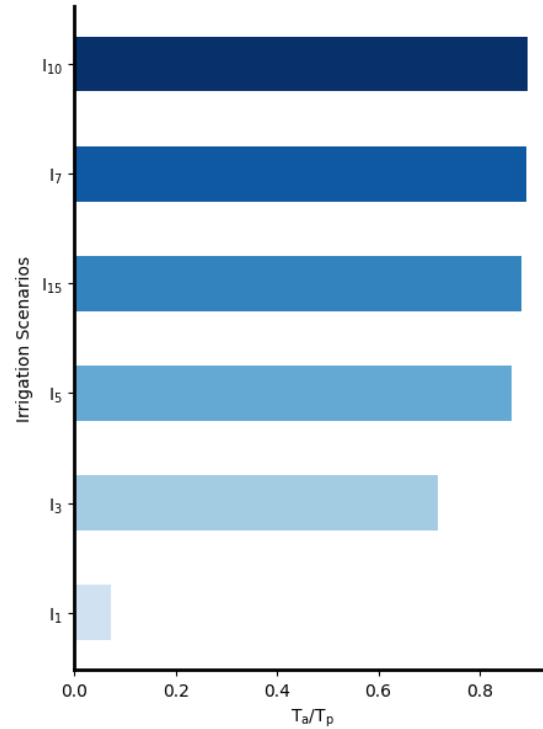


Figure 25. The relative transpiration rate (T_a/T_p) under different irrigation scenarios

7.4. Improved Irrigation Management

Irrigation interval or frequency plays a crucial role in influencing the rates of evaporation, transpiration, and deep percolation. However, optimum irrigation frequency is not constant since it is affected by several variables, such as soil, climate, and crop type. This study utilized the calibrated HYDRUS-1D in simulating the soil water fluxes under specific conditions. Specifically, a one-year-old lemon tree with a root system concentrated within a depth of 0-40 cm was planted in an area characterized by a desert arid environment. The addition of compost at the beginning of experiment altered the soil composition, from sandy soil into sandy loam, particularly in areas where roots are primarily distributed.

Soil evaporation rate is primarily governed by atmospheric conditions (wind, temperature, humidity) and the soil's ability to supply water to meet atmospheric demand (Or &

Lehmann, 2019). In this study, results of simulations showed that, under the same atmospheric demand, soil evaporation decreased as the irrigation frequency decreased. In contrast, transpiration increased as the irrigation frequency decreased. This indicates that soil characteristics played a major role in these processes since the atmospheric demand remained the same.

Frequent irrigation typically utilizes smaller water amount than infrequent irrigation, resulting in shallow irrigation depth. Consequently, in soil characterized by higher water-holding capacity such as loamy soil, most of the water will be located at the upper layer near the soil surface since the created surface wetted radius is small (Amin et al., 2006). This aligns with numerous studies conducted in various climate conditions with the same soil texture, revealing that the proportion of water held in the upper soil layer is larger with frequent irrigation and smaller dose, resulting in increased evaporation (Ertek et al., 2006; Sebastian et al., 2015; G. Zhang et al., 2019). Further, Sebastian et al (2015) found that soil water tension under infrequent irrigation in loamy soil was higher than frequent irrigation, thus favoring higher crop water status. This may explain why transpiration increased with increasing irrigation interval.

Increased irrigation interval with larger dose will create bigger surface wetted radius, allowing water to be redistributed in the deeper soil (Amin et al., 2006) due to saturated upper soil profile, that subsequently resulting in rapid drainage and deep percolation. Deep percolation typically occurs when the soil water content is higher than field capacity. This condition represents steady-state conditions which is considered as the dominant process contributing to deep percolation (Bethune et al., 2008). This study found that deep percolation tended to increase with increasing irrigation water use. This process might

result in nutrient leaching and groundwater pollution if there is the presence of a shallow aquifer.

However, since the value of deep percolation is low compared to another unproductive component of soil water balance (evaporation) and given that most groundwater table in Saudi Arabia are deeper, such attention should be given for addressing evaporation. According to soil water fluxes components, only a small proportion of irrigation water was used by crops for transpiration process, while most of water lost due to evaporation, thus reducing the irrigation efficiency. To overcome this issue, additional practice such as implementation of organic or plastic-film mulching which can reduce soil evaporation and are common in agricultural management, should be considered (Du et al., 2008; Kader et al., 2017; Liao et al., 2021; Qin et al., 2016). This is particularly relevant for loamy soil which has larger characteristic length compared to other soil types (Or & Lehmann, 2019). A characteristic length reflects competition between capillary, gravity and viscous dissipation that eventually determines magnitude of evaporation in layered media (Or et al., 2007). Simply, a larger characteristic length indicates stronger capillary forces acting against gravity to supply water to the surface, thereby sustaining evaporation process (Or & Lehmann, 2019).

The improvement of irrigation water efficiency mainly aims to maximize crop transpiration and reduce soil water loss from soil evaporation and deep percolation. As discussed, low irrigation frequency might result in higher evaporation dan lower percolation, while high irrigation frequency would generate lower evaporation and higher percolation. In order to determine the most optimum scenario, this study utilized T_a/T_p to define the threshold of irrigation frequency. The most optimized irrigation water scenario was determined when

the transpiration is maximum since this criterion is closely associated with crop growth and yield.

It should be noted that a suitable irrigation interval depends on several factors, such as meteorological conditions and soil texture. This study aimed to mimic the real conditions in Saudi Arabia, especially in the Arabian platform which is characterized by a desert arid climate and sandy soil. Considering that the Saudi Green Initiative has objective to plant 4 million lemon trees across the Kingdom to enhance biodiversity and improve fruit self-sufficiency, the findings of this study could be applied to support that initiative while at the same time improving irrigation water use efficiency. In conclusion, the I_{10} scenario needs to be taken into consideration particularly in areas with similar climate and soil characteristics since it has higher T_a/T_p value.

CONCLUSIONS

- 3D and 4D geoelectrical geophysical method were successfully applied to characterize and monitor the root zone of a lemon tree.
- High-resolution geoelectrical tomographic images were produced, identifying the area of the root zone at the depth slices of 0.25-0.34m and 0.44-0.55m, especially from April-June 2023.
- The tomographic images were distorted during the summer period, particularly from July to September 2023 when the temperature was high.
- The 3D and 4D electrical resistivity imaging were successfully used to estimate the distribution of soil moisture into the subsurface.
- Low-frequency GPR antenna (400 MHz) successfully localizes the zone where fine roots are distributed.
- The observed spatial distribution of the root zone based on the geophysical results, showed that the root zone is concentrated in the upper soil layer and is likely influenced by the type of irrigation used in this experiment (flood irrigation).
- The transformed electrical resistivity values into soil moisture successfully used as an input model for the initial condition of HYDRUS 1D and model calibration.
- The simulated RWU revealed that the morning period (08:00 – 11:00) could be considered the optimal irrigation timing, corresponding to the highest RWU rates.
- RWU zones shifted to lower depths during summer due to increased soil evaporation.
- The calibrated HYDRUS 1D proved to be valuable in simulating the most effective irrigation scenario to support the Saudi Green Initiative.

- Throughout the study period, soil water loss was predominantly caused by soil evaporation under all irrigation scenarios.
- The volume of water lost due to deep percolation was much smaller than that lost through soil evaporation.
- CROPWAT can be considered a reliable tool for decision-makers in managing irrigation scheduling.
- The irrigation period every 10 days (I_{10}) is found to be the optimal irrigation scenario compared to others.

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Curriculum Vitae

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Selected Publications

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| 2024 | Suitability of treated wastewater for irrigation and its impact on groundwater resources in arid coastal regions: Insights for water resources sustainability. https://doi.org/10.1016/j.heliyon.2024.e29320 |
| 2024 | Advancing SDGs: Predicting Future Shifts in Saudi Arabia's Terrestrial Water Storage Using Multi-Step-Ahead Machine Learning Based on GRACE Data. https://doi.org/10.3390/w16020246 |
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