Modeling Soil–Water–Disease Interactions of Flood-Irrigated Mandarin Orange Trees: Role of Root Distribution Parameters


Variably saturated flow models that simulate soil–water–plant interactions within the rhizosphere largely ignore the effect of plant health. This makes it difficult for them to effectively simulate root water uptake (RWU) and implement alternate management practices for diseased trees. This research was aimed at understanding the hydrological and plant controls on RWU simulations dominated by the health of the tree using experimental and numerical frameworks. Two research plots, one around a healthy mature and the other around a diseased mature (Phytophthora spp. affected) orange tree (Citrus reticulate Blanco), in the Vidarbha region of India were considered for our analysis. Three-dimensional electrical resistivity tomography (ERT) performed at the two locations revealed that the soil moisture profiles following irrigation are different between the two plots. A two-dimensional axisymmetric form of Richards’ equation was then solved using HYDRUS (2D/3D) by incorporating a root distribution function. A global sensitivity analysis was performed to identify the root distribution parameters that influence soil moisture simulations. These parameters were then optimized using a genetic algorithm for healthy and diseased conditions. We observed that the diseased orange tree had consumed less water, leaving high soil moisture in the rhizosphere, a condition favorable for the further growth of disease-causing fungi. Hence, managing irrigation water in accordance with RWU patterns is essential for diseased trees. To understand the error propagation in RWU estimation, we simulated RWU from a diseased tree with the optimal parameters derived for a healthy case. Results show that the error in estimating RWU from the model cells progressively increases with radial distance and soil depth.

Abbreviations: DOY, day of the year; ERT, electrical resistivity tomography; RWU, root water uptake; TDR, time domain reflectometry.

Globally, India ranks fourth in orange production, accounting for 7.60% of the world’s tonnage. However, India ranks 6th in orange crop productivity (yield per unit area), accounting for 9.23 t ha⁻¹. The Vidarbha region in Maharashtra is the leading producer of mandarin orange, accounting for 40% of the country’s production with a yield of 6 t ha⁻¹, far below the nation’s average. Low crop yield in Vidarbha is attributed to erratic climate conditions and improper management activities, resulting in the formation and propagation of a water mold disease called root rot (Phytophthora spp.). Under favorable conditions (high soil moisture and cool temperature), the disease-causing fungus produces a large number of motile zoospores that can swim in water and move to the roots. These zoospores contact the root system; they then encyst, germinate, and enter the root tip, resulting in rot of the entire rootlet (Savita and Nagpal, 2012). These root pathogens can damage the tree by decreasing root density and water and nutrient uptake (Duniway, 1971). Hence, the application of irrigation water in accordance with the disease level of the tree is essential in decreasing the intensity of root rot. It is almost impossible to identify early stage symptoms of this disease (which originate in the rhizosphere), making it difficult to implement effective management practices (Jagtap et al., 2012). Late-stage impressions of a disease-affected tree are seen at
the surface, with symptoms such as leafless branches, yellow foliage, shoot dieback, reduced fruit size and yield, thin canopy, failure to make new growth, and reduced water and nutrient uptake leading to wilting (Zekri and Rouse, 2002). A significant decrease in orange production resulting from these pathogens has been reported in the high-rainfall subtropics of the world (Das et al., 2011; Jagtap et al., 2012; Graham and Feichtenberger, 2015). A number of researchers have addressed the management of Phytophthora-affected orange trees using chemical and biological treatments, with less attention given to comprehending the dominant agroclimatic factors responsible for the decreased RWU. To the best of our knowledge, no significant research has been published on the mechanisms by which the disease-causing pathogens can alter soil–water–plant relations within the rhizosphere. One reason for this is that management and control of Phytophthora spp. in orange trees is largely viewed from the pathology and molecular biology disciplines rather than from agronomy and hydrology (Irey et al., 2006; Kean et al., 2010; Das et al., 2011; Gade, 2012; Jagtap et al., 2012; Graham and Feichtenberger, 2015). Bright et al. (2004) studied the effect of soil, rootstock, and climatic parameters on Phytophthora spp. populations and concluded that molecular biology and the water-holding capacity of fine-textured soils have a profound effect on the growth of disease-causing fungi.

Classical methods of estimating soil moisture in the near-surface zone, such as the gravimetric method (Sharp and Davies, 1985), neutron probes (Robock et al., 2000), and time domain reflectometry (TDR) (Walker et al., 2004; Calamita et al., 2012) are relatively expensive, provide point estimates, and are destructive in nature. In contrast, remote sensing techniques (Schmugge et al., 1976; Dorigo et al., 2015) provide soil moisture distributions across large areas without soil destruction but suffer from the drawback of low resolution and depth of penetration. Because the soil electrical conductivity is a good substitute for moisture content and solute concentration (Banton et al., 1997; Srayeddin and Dousson, 2009; Garré et al., 2011), electrical resistivity tomography (ERT), a noninvasive, proximal, geophysical technique, has been widely used in the recent past to characterize soil–water dynamics within the rhizosphere (Brunet et al., 2010; Brillante et al., 2015). Many studies have shown that ERT can be suitably applied to monitor soil moisture and RWU patterns at local to field scales (Werban et al., 2008; Amato et al., 2010; Garré et al., 2011; Beff et al., 2013; Boaga et al., 2013; Cassiani et al., 2015). However, ERT-derived soil moisture data have to be validated at spatially distributed point locations (gravimetric or TDR probes) before numerically characterizing the root zone water distribution (Schwartz et al., 2008; Boaga et al., 2013; Cassiani et al., 2015).

Quantification of RWU is not only significant in characterizing hydrologic fluxes but also helps in implementing sound water management policies with regard to production and environmental impacts. Root water uptake can be simulated considering lumped (mesoscopic) or distributed (macroscopic) parameter models (Volpe et al., 2013; Manoli et al., 2014). In a mesoscopic approach (Feddes and Raats, 2004; Vogel et al., 2016), individual roots of a tree are idealized as an infinitely long cylindrical sink of constant radius with convergent inward radial flow, while in a macroscopic approach (Skaggs et al., 2006; Deb et al., 2013), a distributed sink term representing root extraction is explicitly added to the governing water flows such as Richards’ equation. Owing to the ease in obtaining model parameters, macroscopic or root-system approaches are more common and popular in simulating RWU response (Šimůnek et al., 2008; Deb et al., 2013; Fan et al., 2015). For isolated trees in large monocultures wherein the RWU is complex, a multidimensional approach considering variably saturated flow is more appropriate (Green and Clothier, 1999; Vrugt et al., 2001a; Deb et al., 2013).

This research aimed at understanding the soil–water–disease interactions of orange trees from a hydrological perspective. Two experimental plots, one around a healthy, mature tree and another around a diseased, mature orange tree were considered for our analysis. Dynamic changes in subsurface soil moisture content following irrigation were monitored at the two plots using a three-dimensional ERT setup. Soil moisture profiles within the active root zone differed greatly between the two plots, confirming spatiotemporal anomalies in RWU characteristics. To understand the controlling factors on water fluxes within the root zone dominated by the health of the orange tree, a two-dimensional axisymmetric form of the soil water flow model with a root distribution function proposed by Vrugt et al. (2001b) was numerically solved using HYDRUS (2D/3D). A global sensitivity analysis was performed to understand the role of root distribution parameters on model simulations. Optimal root distribution parameters for the two conditions were obtained using a genetic algorithm, with the objective of minimizing the measurement of model-simulated soil moisture discrepancies. Finally, irrigation practices in accordance with RWU patterns (monitored via soil moisture) are suggested for effective management of diseased orange trees.

**Materials and Methods**

**Site Description**

Two research plots, one at a healthy and other at a diseased mature orange tree situated at Nagziri village in Warud Taluk, Maharashtra, India (21°27′5″ N, 78°9′12″ E, elevation 460 m asl) were considered for our analysis. Table 1 provides the characteristics of the orange trees used in the field experiment. The study area is a part of Vidarbha, known for mandarin orange production in India. The Vidarbha region is characterized by a semiarid climate, with average annual precipitation ranging from 950 to 1250 mm, maximum temperature varying from 32 to 45°C, and minimum temperature varying from 15 to 24°C (Central Ground Water Board, 2013). The humidity of the region varies from 35% in summer to 73% in the monsoon season. The study area forms...
According to FAO soil taxonomy, the soil is classified as a verti-

cal.

Agriculture is the main consumer of groundwater in the study

area, with water drawn mostly from upper weathered and frac-
tured aquifers.

In south and central India, mandarin oranges bloom thrice a year.
The February flowering is known as *ambe bahar*, the June flower-
ing as *mrig bahar*, and the October flowering as *bast bahar*. Due
to limited water resources, farmers of the region prefer *mrig bahar*,
which does not demand much water in summer months. Orange
trees of the region are planted at a spacing of 5 m along both row
and column directions. Water requirements of orange trees are
generally higher than most other subtropical crops due to recur-
rent growth and development. Irrigation in the region is practiced
through a drip system in winter and the flood system in the pre-
summer months at 15- to 20-d intervals. The water requirement of
a mature orange tree varies from 900 to 1100 mm yr$^{-1}$. A healthy
mature orange tree of the region can produce 500 to 800 fruits
every year, with an average yield of 11.86 t ha$^{-1}$.

Because the ERT experiments were carried out during pre-summer
months, the plots were flood irrigated at a 15- to 20-d interval to
an average depth of 35 mm. A total of four irrigations were applied
during the monitoring period. The ERT measurements were taken
before and after irrigation at regular intervals until the moisture
was completely drained out of the root zone. Four calibrated TDR
soil moisture probes were placed underneath each plot at depths
of 15, 30, 45, and 60 cm to validate the ERT data.

**Laboratory Estimation of Soil Properties**

Undisturbed soil samples were collected in cylindrical cores
(13-cm height and 10-cm diameter) from four depth horizons
(4–17, 17–30, 30–43, and 47–60 cm) underneath the experi-
mental plots. These samples were used to estimate physical and
electrical properties in the laboratory under controlled conditions.
According to FAO soil taxonomy, the soil is classified as a verti-
sol with high expansive clay content and water holding capacity
(Dudal, 1965; Virmani et al., 1982). The soil has a swell index of
55%, and the physical properties estimated in the laboratory are
provided in Table 2. The shape parameters of the soil moisture characteristic were obtained by fitting the van
Genuchten–Mualem model for the soil horizon at the
30-cm depth (representative of all soil layers). A plastic
cylinder of 5-L capacity with top and bottom end plates
was filled with compacted soil so that field conditions
were replicated. Tensiometers filled with blue liquid
(to avoid algae formation) were used to record the soil
matric potential ($\psi$) during experimentation. Water
used to irrigate the orange fields has been used in satu-
rating the soil columns. The electrical conductivity of the
water was measured as 0.063 S m$^{-1}$. Soil moisture was
decreased from saturated water content ($\theta_s$) to residual
water content ($\theta_r$) in stages by naturally allowing pore water to
evaporate into the air. During each stage of drying that took about
24 h, both volumetric water content (gravimetric) and soil suction
(tensiometer) were accurately measured following an equalization
period (Lourenço, 2008). The van Genuchten–Mualem model
shape parameters $\alpha_v$ and $n$ were estimated by fitting the experi-
mental data using the RETC code (van Genuchten et al., 1991)
that considers the constitutive relationships given by

\[
\theta(\psi) = \begin{cases} 
\theta_s + \frac{\theta_s - \theta_r}{1 + (\beta \psi)^{1/m}}^
u & \text{if } \psi < 0 \\
\theta_r & \text{if } \psi \geq 0 
\end{cases}
\]

\[
K(\psi) = K_s \left[ 1 - \left( \frac{\psi}{\psi_m} \right)^m \right]^{n} 
\]

where $\theta_s$ and $\theta_r$ are the residual and saturated soil water contents
($\text{cm}^3 \text{ cm}^{-3}$), respectively; $\alpha_v$ is the reciprocal of the air-entry pres-
sure head ($\text{cm}^{-1}$); $m = 1 - 1/n$; $n$ is the pore-size distribution
index (dimensionless); $S_e$ is effective saturation (dimensionless);
$I$ is a pore-connectivity parameter (dimensionless); and $K_s$ is the
saturated hydraulic conductivity ($\text{cm} d^{-1}$).

The nonlinear relation between resistivity and soil moisture for
field soils was generated following ASTM guidelines (ASTM,
2012). An acrylic cylindrical mold (180-mm length and 80-mm
diameter) with porous plates at the ends was filled with a fully

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Layer 1 (4–17 cm)</th>
<th>Layer 2 (17–30 cm)</th>
<th>Layer 3 (30–43 cm)</th>
<th>Layer 4 (47–60 cm)</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk density, g cm$^{-3}$</td>
<td>1.64</td>
<td>1.75</td>
<td>1.77</td>
<td>1.82</td>
<td>gravimetric</td>
</tr>
<tr>
<td>Moisture content</td>
<td>0.43</td>
<td>0.46</td>
<td>0.45</td>
<td>0.47</td>
<td>gravimetric</td>
</tr>
<tr>
<td>Porosity</td>
<td>0.54</td>
<td>0.55</td>
<td>0.54</td>
<td>0.53</td>
<td>gravimetric</td>
</tr>
<tr>
<td>Specific gravity</td>
<td>2.51</td>
<td>2.58</td>
<td>2.62</td>
<td>2.56</td>
<td>density bottle</td>
</tr>
<tr>
<td>Composition, %</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sand</td>
<td>10.9</td>
<td>12.4</td>
<td>14.4</td>
<td>17.9</td>
<td>wet sieve and hydrometer</td>
</tr>
<tr>
<td>Silt</td>
<td>34.7</td>
<td>36.1</td>
<td>37.1</td>
<td>36.2</td>
<td></td>
</tr>
<tr>
<td>Clay</td>
<td>54.3</td>
<td>51.2</td>
<td>48</td>
<td>45</td>
<td></td>
</tr>
</tbody>
</table>

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Table 1. Physical, phenological, and health characteristics of the man-
darin orange trees considered for field experimentation.

<table>
<thead>
<tr>
<th>Experimental plot</th>
<th>Tree age (yr)</th>
<th>Leaf area index†</th>
<th>Disease symptoms</th>
<th>Yield (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy, mature</td>
<td>16</td>
<td>2.27</td>
<td>none</td>
<td>75</td>
</tr>
<tr>
<td>Diseased, mature</td>
<td>16</td>
<td>1.71</td>
<td>yellow foliage, gum formation at trunk</td>
<td>50</td>
</tr>
</tbody>
</table>

† LAI values are averaged across the simulation period (Days of the Year 31–116).
We developed a three-dimensional protocol with a dipole–dipole configuration to suit the grid architecture and validated using a series of two-dimensional sections before taking actual measurements. An L1 norm regularized inversion was performed on the filtered dataset to represent the subsurface resistivity structure. Each tree was provided with TDR moisture probes at four depth levels (15, 30, 45, and 60 cm below ground level) along the outer edge of the grid (Fig. 1). The ERT-derived soil moisture data were in close agreement with TDR measurements (Fig. 2) and hence were considered as observed soil moisture for use with HYDRUS (2D/3D) calibration. Three tensiometers were installed beneath each plot (at depths of 20, 40, and 90 cm, with a horizontal spacing of 20 cm) to monitor drainage fluxes. The depths were determined in such a way that the hydraulic gradient across the root zone was completely captured. Water fluxes crossing the bottom boundary were estimated using Darcy’s law (Whitaker, 1986).

### Numerical Simulation

Because ERT-derived soil moisture profiles are symmetrical in the $x$–$y$ plane (Fig. 3), an axisymmetrical form of Richards’ equation describing variably saturated flow was used to simulate RWU from the orange trees. We used HYDRUS (2D/3D) to simulate the transient movement of water flow and RWU processes (Šimůnek et al., 2006; Šimůnek and Hopmans, 2009) in a homogeneous, isotropic, variably saturated flow domain. Details on HYDRUS (2D/3D) simulation can be found in Šimůnek et al. (2006, 2012).

Neglecting the effect of the air phase on water flow, the governing equation for variably saturated flow is

$$\frac{\partial \theta}{\partial t} = \frac{1}{r} \frac{\partial}{\partial r} \left( r K \frac{\partial \psi}{\partial r} \right) + \frac{\partial}{\partial z} \left( K \frac{\partial \psi}{\partial z} \right) + \frac{\partial K}{\partial z} \cdot S(\psi, r, z)$$

where $t$ is simulation time (d); $r$ is the radial distance from the trunk (cm); $z$ is the simulation step in the vertical direction, positive upward (cm); $\psi$ is the pressure head (cm); $K$ is the unsaturated hydraulic conductivity function (cm d$^{-1}$); and $S(\psi, r, z)$ is RWU from the model, represented as a sink term ($\text{cm}^3 \text{cm}^{-3} \text{d}^{-1}$) given by

$$S(\psi, r, z) = \alpha(\psi, r, z) \times S_p(r, z) = \alpha(\psi, r, z) \times b(r, z) \times T_p \times L$$

where $\alpha(\psi, r, z)$ is the water stress response function (dimensionless), $S_p(r, z)$ is the potential RWU ($\text{cm}^3 \text{cm}^{-3} \text{d}^{-1}$), $b(r, z)$ is the normalized water uptake distribution ($\text{cm}^{-2}$), $T_p$ is the potential transpiration rate ($\text{cm} \text{d}^{-1}$), and $L$ is the surface length associated with transpiration (cm). We adopted the two-dimensional axisymmetric root distribution function proposed by Vrugt et al. (2001b) in estimating the normalized water uptake distribution:

$$b(r, Z) = \left[ \frac{1 - Z}{Z_m} \right] \left[ \frac{1 - \frac{r}{R_m}}{Z_m} \right] \times \exp \left[ - \frac{p_Z}{Z_m} \left| Z - Z_m \right| + \frac{p_e}{R_m} \sigma^* - r \right]$$

where $Z_m$ (cm) is the maximum rooting depth, $p_Z$ (dimensionless) and $\sigma^*$ (cm) are empirical parameters, $R_m$ (cm) is the maximum rooting length in the radial direction, $r$ (cm) is the radial distance

### Table 3. Waxman and Smits (1968) model parameters fitted to soils of different horizons along with measures of fitness.

<table>
<thead>
<tr>
<th>Sample depth</th>
<th>$a$</th>
<th>$c$</th>
<th>$b$</th>
<th>RMSE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>cm</td>
<td>S m$^{-1}$</td>
<td>S m$^{-1}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4–17</td>
<td>1.48</td>
<td>2.45</td>
<td>0.038</td>
<td>0.012</td>
<td>0.98</td>
</tr>
<tr>
<td>17–30</td>
<td>1.19</td>
<td>2.19</td>
<td>0.045</td>
<td>0.005</td>
<td>0.99</td>
</tr>
<tr>
<td>30–43</td>
<td>0.61</td>
<td>1.71</td>
<td>0.051</td>
<td>0.011</td>
<td>0.97</td>
</tr>
<tr>
<td>47–60</td>
<td>0.59</td>
<td>2.29</td>
<td>0.050</td>
<td>0.010</td>
<td>0.96</td>
</tr>
</tbody>
</table>
from the origin of the tree, and \( p_r \) (dimensionless) and \( r^* \) (cm) are additional empirical parameters. These empirical parameters were considered so as to provide zero RWU beyond \( Z_m \) to account for asymmetrical RWU in the vertical and radial directions and to allow maximum RWU within 0 to \( Z_m \) (Vrugt et al., 2001b). In this case, \( b(r,z) \) (dimensionless) defines the two-dimensional spatial distribution of RWU from the model. Normalizing the uptake distribution ensures that \( b(r,z) \) integrates to unity over the flow domain. The numerical grid considered with HYDRUS (2D/3D) simulation is represented in Fig. 4. Even though a 1.5-m depth of the model domain was discretized, moisture profile variation in the top 80-cm depth (containing the active root zone) was considered for model calibration. Global sensitivity analysis was performed using the Sobol’ algorithm (Sobol’, 1993) to understand the role of root distribution parameters in simulating soil moisture from healthy and diseased trees. A total of 1000 parameter sets were considered to develop the first-order and total-order sensitivity indices (Saltelli et al., 2010; Hartmann et al., 2018). The contributions of individual parameters and their interactions with other parameters was analyzed to discard the model insensitive parameters. Model calibration and parameter estimation were then performed using a genetic algorithm by minimizing the error in HYDRUS-simulated moisture content.

**HYDRUS (2D/3D) Parameterization**

For \( \alpha(\psi; r, z) \), the functional form of RWU proposed by Feddes et al. (1978) with no water stress compensation was used in the simulation. The water stress response function \( (\alpha) \) denotes the factor by which actual RWU is reduced and can be described using a piecewise linear relation:
where $\psi_1$, $\psi_2$, $\psi_3$, and $\psi_4$ are the threshold parameters. Water uptake is at the potential rate when the pressure head is between $\psi_2$ and $\psi_3$, decreases linearly when $\psi > \psi_2$ or $\psi < \psi_3$, and becomes zero when $\psi \leq \psi_4$ or $\psi \geq \psi_1$. The following Feddes model parameters applicable for orange trees (Phogat et al., 2013, 2014) were used in estimating the water stress response factor: $\psi_1 = -10$, $\psi_2 = -25$, $\psi_3_{\text{max}} = -200$, $\psi_3_{\text{min}} = -1000$, and $\psi_4 = -8000$ cm.

Because HYDRUS (2D/3D) requires daily evaporation ($E_p$) and transpiration ($T_p$) to be input separately along the atmospheric boundary, we first estimated daily reference evapotranspiration ($ET_0$) using the FAO-based Penman–Monteith equation (Allen et al., 1998). Daily meteorological data were collected from an automatic weather station located at about 100 m from the experimental site. The $ET_0$ was further partitioned into $E_p$ and $T_p$ by considering the measured leaf area index values (Ritchie, 1972) and is given by

$$E_p = ET_0 \exp(-kLAI)$$

and

$$T_p = ET_0 - E_p$$

where $k$ is a constant defining the radiation extinction by the canopy. We used a value of 0.39 for $k$ following Campbell and Norman (1998).

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**Results and Discussion**

Pedo-physical and pedo-electrical relations were derived under controlled laboratory conditions to understand the soil characteristics. The ERT-derived soil moisture profiles are presented to help understand subsurface soil water dynamics for healthy and diseased orange trees. Finally, numerical results from HYDRUS (2D/3D) are presented to evaluate the role of root distribution parameters on RWU simulations dominated by the health of the tree.

**Soil Physical and Electrical Properties**

Unsaturated hydraulic properties of the soil were estimated in the laboratory considering the drying phase of the water retention curve. The van Genuchten–Mualem soil-water characteristic curve was well fitted to the data ($R^2 = 0.87$) with the model parameters of $a_v = 0.01169$ cm$^{-1}$ and $n = 1.64$ (Fig. 5). The $K_s$ of the soil was estimated using a constant-head permeameter and found to be 11.04 m d$^{-1}$. The initial value of the pore connectivity parameter, $l$, was considered to be 0.5 (Mualem, 1976).

Unsaturated electric properties were estimated for each soil horizon (4–17, 17–30, 30-43, and 47–60 cm) by fitting the Waxman–Smits (1968) constitutive relations to the data (Fig. 6). The model assumes a constant soil solution conductivity, and hence any change in electrical conductivity can be attributed solely to the changes in soil moisture. This assumption is meaningful because both the water used for irrigation and the pore water resulted in the same electrical conductivity. Electrical resistivity at saturation ranged from 3.75 to 5.22 $\Omega$ m, with no apparent lithological anomalies observed between the layers. The Waxman–Smits model parameters for the field soils are given in Table 3. From this, it is evident that electrical resistivity variation with soil moisture can be best approximated using a power law function ($R^2 > 0.96$). The
developed equations can be used with ERT data to generate soil moisture profiles that can be readily used with numerical calibration. For depths beyond 60 cm (which are not of primary interest), model parameters corresponding to the 47- to 60-cm soil horizon were utilized in generating the moisture profiles. Pore water conductivity was measured to be 0.063 S m$^{-1}$, confirming the absence of dissolved solids (Rhoades, 1996). The soil moisture profiles generated from the proposed constitutive relations were in agreement with published reports and applicable for vertisols (Amidu and Dunbar, 2007).

**Soil Moisture Profiles Using Electrical Resistivity Tomography**

We performed three-dimensional ERT at the two experimental plots, which are separated by 5 m, for different time periods (time-lapse ERT) to understand the spatiotemporal variation in soil moisture. The schedule of water management and ERT data acquisition for the two plots is given in Table 4. During each irrigation, the plots were flooded on the central 7.84-m$^2$ region at a constant rate of 35 L min$^{-1}$ for about 10 min to replicate field practices. The field capacity of the soil was reported to be 0.42. All ERT sections resulted in an RMSE (between successive iterations) of $<3\%$, confirming the
effectiveness of the inversion algorithm. Typical ERT-derived soil moisture profiles for healthy and diseased orange trees is given in Fig. 3. These figures have opened up many interesting research questions. A clear and sharp soil moisture front was observed (prior to irrigation) at a depth range of 40 to 45 cm for the healthy tree and 35 to 40 cm for the diseased tree. Because no lithological anomalies were reported (Fig. 6), this moisture change can be attributed to root zone activity. This confirms that surface ERT is able to image the soil moisture interface separated by active roots. For the same applied irrigation water and soil water evaporation losses, relatively higher soil moisture values for a diseased tree following irrigation were observed due to less RWU. A long time (about 20 d) after irrigation, the soil moisture profiles were similar to those prior to irrigation, completing one irrigation cycle. Even though healthy and diseased trees have recorded similar temporal moisture patterns, their values differ marginally. A low soil moisture (close to the wilting point) in the active root zone long after irrigation is in congruence with the frequency of irrigation (15–20 d) practiced in the region. It is important to note that we are not quantifying the intensity of the disease using pathological studies. A diseased tree considered in the present research has been “moderately” affected by *Phytophthora* spp., showing yellow foliage and gum formation at the trunk of the tree. A comprehensive understanding of time-lapse ERT profiles compared with the disease level (mild to moderate to severe) of the tree might help in modifying RWU models to account for the health of the tree. A \( \chi^2 \) test of homogeneity performed on ERT-derived soil moisture for the healthy and diseased trees confirmed that the two datasets are significantly different (\( \alpha = 0.05, \text{df} = 4 \)). Hence, we claim that considering the same root distribution parameters in simulating RWU might lead to erroneous results, particularly for diseased trees.

**Numerical Simulation with HYDRUS (2D/3D)**

To understand the role of root distribution parameters on RWU simulations dominated by the health of the tree, we simulated the
field conditions using a numerical setup in HYDRUS (2D/3D). The numerical model with appropriate atmospheric and drainage boundary conditions (Fig. 4) was run on a daily time step for an 85-d period (Day of the Year [DOY] 31–116, viz., 31 Jan. 2016–25 Apr. 2016). The domain was discretized in such a way that the grid cells of ERT and HYDRUS (2D/3D) models coincided to the greatest extent possible to minimize interpolation errors. Results of the global sensitivity analysis (Fig. 7) conclude that the parameters defining the shape of the root distribution function (viz., $p_z$ and $pr$) are insensitive to RWU. The calibration was initiated by matching HYDRUS (2D/3D) simulated moisture with ERT data at the common grid cells. A total of 210 calibration points having nodes taken from six depth levels (10, 20, 30, 40, 50, and 60 cm), six radial distances (17, 44, 63, 89, 105, and 120 cm from the trunk), and nine time steps (DOY 33, 72, 73, 74, 94, 95, 114, 115, and 116) were considered. Model parameterization and optimization were done using genetic algorithms by considering the model sensitive parameters (viz., $Z_m$, $z^*$, $R_m$, and $r^*$) to vary within the prescribed range (Vrugt et al., 2001a). The remaining parameters that are insensitive to soil moisture (viz., $p_r$ and $p_z$) were taken from the literature (Vrugt et al., 2001a). Optimal root distribution parameters that resulted in a close match between observed and simulated moisture and the range of the a priori distribution are given in Table 5. From this, it is clear that a healthy tree has

### Table 4. Schedules of irrigation and electrical resistivity tomography (ERT) data acquisition for healthy and diseased orange trees.

<table>
<thead>
<tr>
<th>Case</th>
<th>Scenario†</th>
<th>Date of observation</th>
<th>Start–end time for ERT survey‡</th>
<th>Start–end time of irrigation‡</th>
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</thead>
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<td></td>
<td>A12</td>
<td>2 Feb. 2016</td>
<td>08:00–8:25</td>
<td>09:30–09:55</td>
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<tr>
<td>II</td>
<td>BI</td>
<td>12 Mar. 2016</td>
<td>17:30–17:55</td>
<td>16:00–16:25</td>
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<td>14 Mar. 2016</td>
<td>07:00–07:25</td>
<td>07:50–08:15</td>
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<tr>
<td>III</td>
<td>BI</td>
<td>4 Apr. 2016</td>
<td>09:00–9:25</td>
<td>10:15–10:40</td>
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<tr>
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<td>18:00–18:25</td>
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<td>24 Apr. 2016</td>
<td>09:15–09:40</td>
<td>08:15–08:40</td>
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</tbody>
</table>

† BI, before irrigation; A11, just after irrigation; A12, long time after irrigation.
‡ All times are in Indian Standard Time.

![Fig. 7. Total and first-order sensitivity indices of root distribution parameters for healthy (left) and diseased (right) orange trees: maximum rooting depth, $Z_m$; maximum rooting length in the radial direction, $R_m$; and empirical parameters $z^*$ and $r^*$. The influence of the shape parameters $p_z$ and $pr$ on model simulations was negligible and they were hence discarded from the optimization.]
extended active roots in both radial and depth directions. A greater depth of the active root zone for a healthy tree (45.18 cm) compared with a diseased tree (38.71 cm) is in agreement with the moisture front depicted by ERT (Fig. 3). Even though the method and amount of irrigation were the same, clear distinct uptake patterns were observed between the two plots. Overall, HYDRUS (2D/3D) was able to capture the soil moisture distribution for healthy \( R^2 = 0.81; \text{RMSE} = 0.025; n = 210 \) and diseased \( R^2 = 0.76; \text{RMSE} = 0.032; n = 210 \) orange trees (Fig. 8). Temporal changes in HYDRUS (2D/3D) simulated RWU lumped throughout the entire flow domain at the two plots are given in Fig. 9. A diseased tree consistently recorded low RWU during the simulation, although some anomalies were observed at the end.

Error Propagation with Root Water Uptake Simulations

To quantify the error (the difference between ERT-derived and HYDRUS-simulated soil moisture) propagated in RWU simulation models, we simulated a diseased orange tree using the optimal parameters derived for healthy and diseased conditions (Table 5). Simulation results under both cases are shown in Fig. 10. We observed a systematic propagation of error with radial distance and depth. The error in simulating RWU is high at large depths and radial distances. In the temporal domain, a diseased tree simulated with optimal root distribution parameters of a healthy case has a slightly deviated soil moisture profile following irrigation. Similar results were observed for two other cases (Table 4). This confirms that, if root distribution parameters are not properly accounted, HYDRUS (2D/3D) underpredicts soil moisture from diseased trees. It can also be observed that the highest RWU for a diseased tree occurs at relatively shallower depths and shorter radial distances than for a healthy tree (Table 5). This may be because the Phytophthora pathogens are active in the vicinity of the active root zone, causing a significant reduction in RWU (Young and Garnsey, 1977). Overall, a Phytophthora-affected orange tree consumes about 16% less RWU than a healthy tree, keeping all other factors the same. This leaves higher moisture levels (for a given irrigation amount) in the active root zone, a condition favorable for the growth and propagation of the disease-causing fungus. Hence, irrigation management of diseased trees should be done by progressively wetting the soil from the outer periphery to the trunk and by continuously monitoring the soil-water fluxes, which aids in understanding the growth of disease-causing fungi.

Limitations of Research

We neglected the effects of pore water conductivity changes from the observed dynamics of the system. This assumption is meaningful because both the irrigation and extracted pore water have shown the same electrical conductivity. Also, ERT-derived soil moisture profiles are in agreement with TDR measurements at all moisture contents. Because the electrodes used in an ERT survey are buried in the ground for the entire monitoring period (to minimize data noise), only two representative orange trees were considered in this research. However, repeatability of the ERT experiments with four
scenarios (Table 4) has improved our confidence in the simulations. The instrument cannot handle borehole electrodes, and hence the ERT experiments were restricted to the surface. To overcome this, we considered longer sectional spreads, which do not lose sensitivity at the depths required for RWU analysis. Root water uptake is largely dependent on plant transpiration, root distribution, and the soil water potential (Šimůnek et al., 1995). An accurate estimation of plant transpiration using sap flow measurements (Lu et al., 2002) and root morphology can improve numerical simulations. Due to various constraints, we were unable to physically measure sap flows from the roots, which could back up HYDRUS(2D/3D) simulations. However, sap flow was estimated as a residual from

Fig. 9. HYDRUS (2D/3D) simulated root water uptake (RWU) from the flow domain for healthy (blue) and diseased (red) orange trees (simulation period: Days of the Year [DOY] 31–116).

Fig. 10. Propagation of error with time (left, in Days of the Year [DOY]), radial distance from the trunk (middle), and depth (right) when simulating root water uptake (RWU) of a diseased tree with diseased (top) and healthy (bottom) root distribution parameters. The term error denotes the deviation of soil moisture from electrical resistivity tomography (ERT) by HYDRUS (2D/3D) at all calibration target locations.
the water balance following each irrigation and found to be in agreement with simulations.

**Conclusion**

The Vidarbha region in Maharashtra, India, is witnessing a continuous decrease in mandarin orange crop yield due to severe climate extremes, improper water management, and propagation of *Phytophthora* root rot, a water mold disease. The first visible impression of this disease is seen at the surface a long time after the initial root attack, making it difficult to regain the health of the tree. Hence, disease prediction and propagation models that can simulate soil–water–disease interactions are vital for improving crop productivity. This research provides an insight into understanding the hydrological and plant controls of disease-affected trees using experimental and numerical frameworks. Two research plots, one around a healthy mature tree and the other around a diseased mature orange tree were considered in this study. A three-dimensional ERT setup with an orange tree at the center was laid out to monitor soil water dynamics in response to irrigation. Pdeo-electrical relations were obtained by considering the Waxman–Smits model. Soil moisture profiles following irrigation were observed to clearly distinguish between the two plots. A two-dimensional axisymmetric form of Richards’ equation was then numerically solved using HYDRUS (2D/3D) to simulate soil moisture and RWU in the rhizosphere. Global sensitivity analysis revealed that the empirical parameters describing the shape of the root distribution function have an insignificant effect on simulations. Model calibration and parameter optimization was done with the sensitive parameters using a genetic algorithm to derive optimal root distribution parameters for healthy and diseased trees. A diseased orange tree consumes less water, leaving high soil moisture in the rhizosphere, a condition favorable for the growth of disease-causing fungi. Irrigation application in relation to disease intensity is suggested for effective management of diseased orange trees.

**Acknowledgments**

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