Deep drainage reduces agricultural water productivity under cropland recently converted from native desert soils (i.e., young cropland) and increases the risks of nutrient and pesticide leaching into groundwater in the desert-oasis ecotone. However, the deep drainage rates under young cropland in these oasis environments remain unclear, especially for winter irrigation, a common practice in Northwest China. The objective of this study was to estimate the deep drainage rate using the HYDRUS-1D model based on soil moisture data in the deep vadose zone. Soil moisture at depths ranging from 0 to 200 cm was measured using HydraProbe II soil sensors in maize \((Zea \text{ mays} \text{ L.})\) and wheat \((Triticum \text{ aestivum} \text{ L.})\) fields in 2015 and 2017, respectively. Using a novel simulation approach based on soil moisture data in the deep vadose zone, the HYDRUS-1D model provided reliable estimates of deep drainage as confirmed by comparison with estimates from the soil water balance method and prior studies in the region. The annual deep drainage averaged 468 mm, and the annual deep drainage coefficient averaged 43% in the young croplands. The winter irrigation amount averaged 265 mm, and the deep drainage coefficient during winter averaged 21% in the young croplands. The sandy soil of the young cropland and inefficient irrigation scheduling are detrimental to water conservation, causing relatively large deep drainage losses and enhancing the risks of groundwater pollution.

Abbreviations: MAE, mean absolute error.

In the desert-oasis ecotone of Northwest China, environmental risks to agriculture, such as water shortage, remain serious and limit the increase of agricultural productivity (Kang et al., 2017; Zhao et al., 2018). The risks of water shortage are increased and water productivity is decreased by excessive cropland water losses, such as high rates of deep drainage. Deep drainage (potential groundwater recharge) refers to downward soil water flux from the bottom of the root zone to the deep vadose zone (Healy, 2010; Min et al., 2017; Wohling et al., 2012). When deep drainage rates are large due to improper irrigation scheduling, nitrate may also be flushed out of the root zone into the deep vadose zone, and the leached nitrate may ultimately move to the aquifer (Min et al., 2018; Yang and Liu, 2010; Yuan et al., 2017). In the desert-oasis region of Northwest China, large-scale conversion of virgin desert to land has occurred. The oasis areas (86,000 km²) are now 3.3 times larger than in the early 1950s (Shen et al., 2001; Zhang et al., 2018). Conventional tillage and irrigation management have been continually adopted in the young cropland. The cropland is typically irrigated in winter with the goal to store soil moisture by soil freezing (Li et al., 2018). Moreover, the soil is generally coarse textured, with low organic matter and weak structure (Zhang et al., 2017, 2018). The deep drainage coefficient (i.e., the ratio of deep drainage to water input) under the irrigated croplands in this region is more than 20% in the growing season (Ji et al., 2007; Zhao and Zhao, 2014). This deep drainage compounds the problem of agricultural water shortage in this and similar arid areas. Accurately quantifying deep drainage is essential for improved management of water resources and modeling contaminant transport in the critical zone.
Deep drainage is a complex hydrological process that is affected by precipitation and irrigation, vegetation conditions, and soil and topography factors (Healy, 2010; Min et al., 2017; Wang et al., 2016; Wyatt et al., 2017). Deep drainage can be hampered by low hydraulic conductivity soil layers, which delays replenishment of the aquifer (Sun et al., 2018). The deep drainage rate is strongly influenced by soil water content in the vadose zone. Soil water dynamics in the deep vadose zone are of fundamental importance in deep drainage estimation (Wyatt et al., 2017). Soil water flux varies with soil depth and time affected by variations in water inputs, root uptake, and evapotranspiration. The actual deep drainage rate is difficult to measure and is commonly estimated by inverse modeling (Wang et al., 2016). Therefore, there is typically a relatively large uncertainty in the deep drainage estimation (Healy, 2010; Lin et al., 2013; Min et al., 2017).

Several research approaches have been proposed to estimate deep drainage rate. The main strategies include physical observation methods (Healy, 2010; Rimon et al., 2007), soil water balance (Min et al., 2017; Zhao and Zhao, 2014), tracer methods (Lin et al., 2013; Radford et al., 2009), and numerical modeling (Wang et al., 2016; Wyatt et al., 2017). Each research method has advantages and disadvantages in measuring deep drainage. Wyatt et al. (2017) estimated daily drainage rates at the Oklahoma Mesonet using soil moisture data with site-specific soil hydraulic properties and a unit-gradient assumption. In recent years, numerical modeling has become perhaps the most widely used method to estimate deep drainage (Min et al., 2017; Wang et al., 2016). Wang et al. (2016) used inverse modeling, including vegetation data, for estimating natural groundwater recharge from a large-scale soil moisture monitoring network across Nebraska. The numerical model determined the effect of the root to be too complex to evaluate deep drainage in many areas (Ji et al., 2007; Min et al., 2017; Wang et al., 2016; Zhou et al., 2012). In the desert-oasis region, the deep drainage rate was estimated using soil water balance (Zhao and Zhao, 2014) and numerical modeling (Ji et al., 2007; Zhou et al., 2012). The deep drainage rate under cropland ranged from 20 to ~42% in the growing season (Ji et al., 2007; Zhao and Zhao, 2014). However, the prior deep drainage estimates were restricted to the growing season. Moreover, the deep drainage rate under different croplands varied greatly due to crop type, irrigation amount, fertility level, and field management (Ji et al., 2007; Li et al., 2015a; Zhao and Zhao, 2014). The deep drainage rates under young cropland remains poorly understood, especially for winter irrigation, a common practice in Northwest China. Further studies are needed to better understand the deep drainage process under the young cultivated cropland in the desert-oasis region.

We used a simplified numerical model with the soil moisture data from the deep vadose zone to elucidate the dynamics of soil water flux and to advance our understanding of how agricultural management (i.e., water inputs) affects the deep drainage process in the desert-oasis region. The modeling approach is simple and effective for estimating the recharge to groundwater and the evapotranspiration from soil (Lei et al., 1988). The key concept of our modeling approach is to skip the complexities of the root zone and only model the soil water flow dynamics below the root zone. Soil moisture at depths ranging from 0 to 200 cm was measured in maize and wheat fields in 2015 and 2017. The objective of this study was to better understand the deep drainage process in the vadose zone under typical young irrigated croplands in the desert-oasis ecotone of Northwest China.

Materials and Methods

Study Site Description

The experiment was conducted in the Linze desert-oasis ecotone, which is located in the middle reaches of the Heihe River in the Hexi corridor of Gansu province, China (100°7’ E, 39°20’ N, 1374 m asl) (Fig. 1). The study area belongs to the Linze Inland River Basin Research Station, Chinese Ecosystem Research Network. The study area has a hyper-arid desert climate (United...
Nations Environment Programme, 1992). The study area has an average annual temperature of 7.6\(^\circ\)C, an annual average of 3051 h of sunshine, average annual wind speed of 3.2 m s\(^{-1}\), average annual precipitation of 117 mm (with 70 to 80% occurring from May through September), and average annual pan evaporation of 2388 mm (range, 1965–2010 mm yr\(^{-1}\)). In the desert-oasis ecotone, the soil is generally sandy textured with low organic carbon (5.9 g kg\(^{-1}\)) (Zhang et al., 2018), which is classified as plowed aeolian sandy soil according to the Chinese Soil Taxonomy. These desert soils have been gradually cultivated for agricultural use over the past 20 yr and are considered as young cultivated sandy cropland. The major crops grown include maize and spring wheat. Conventional tillage management and furrow irrigation are the most commonly used production practices in this area (Su et al., 2010). The water used for crop production is taken from the Helhe River.

**Experimental Setup and Measurements**

The study sites include a spring maize field and a spring wheat field. The study sites were adjacent in the Linze Station. Spring maize was sown on 8 Apr. 2015 and harvested on 20 Sept. 2015 and was sown 10 Apr. 2017 and harvested on 23 Sept. 2017. Spring wheat was sown 7 Mar. 2015 and harvested on 20 July 2015 and was sown 10 Mar. 2017 and harvested on 23 July 2017. During the growing season, crops are typically irrigated at least 10 times, depending on crop and soil conditions (Zhang et al., 2016). Typically, croplands are also irrigated to store soil water in winter. The water table depth was relatively stable at a depth of 400 cm.

The soil at the two sites was sampled every 20 cm in the 0- to 200-cm soil profile to analyze soil properties. Soil particle size distribution was analyzed using the pipette method (Gee and Bauder, 1986). Bulk density was measured using the thermogravimetric method on an intact soil sample obtained by manually inserting a ring (5 cm in diameter, 5 cm in height) into the undisturbed soil. Volumetric water content at −33 and −1500 kPa was determined using a high-speed centrifuge (H-1400pF, Kokusan). The basic soil properties are summarized in Table 1.

Soil moisture measurements in the two study sites were conducted in 2015 and 2017. Soil moisture was measured with the HydraProbe II soil sensor (Stevens Water Monitoring Systems) at depths of 20, 40, 60, 100, 120, 140, 160, and 200 cm in the spring maize field. Soil moisture was measured with the HydraProbe II soil sensor (Stevens Water Monitoring Systems) at depths of 20, 40, 60, 100, 120, 140, and 180 cm in the spring wheat field. Meteorological data (e.g., daily net radiation, air temperature, wind velocity, relative humidity, and precipitation) were monitored from the Linze Weather Station. The weather station was about 30 m away from the experimental croplands.

**HYDRUS-1D Model**

The HYDRUS-1D model is a one-dimensional physically based model that can be used to simulate water, heat, and solute transport (Šimůnek et al., 2005). The van Genuchten–Mualem model (Mualem, 1976; van Genuchten, 1980) was used to simulate soil hydraulic properties. The governing equation described by Richards’ equation (Richards, 1931) in its one-dimensional form was used to model water flow throughout the soil profile.

The key concept of our modeling approach is to skip the complexities of the root zone and instead model the relatively simple soil water flow dynamics below the root zone. For each field we chose as our upper boundary a sensor depth below which root water uptake was expected to be negligible based on prior studies. In the spring maize field, the soil depth of 140 cm was set as the upper boundary. In the spring wheat field, the soil layer at a depth of 120 cm was set as the upper boundary. Beneath those depths, we simulated a one-dimensional vertical soil profile with a thickness of 60 cm. We assumed that the drainage rates at a depth of 180 to 200 cm were indicative of potential groundwater recharge rates (Li et al., 2015a; Yi, 2015). The initial condition for the simulations was soil water content in the upper boundary before the simulation. The upper boundary condition was defined as a variable pressure head. The lower boundary was simulated as free drainage. The capillary rise of water was negligible because the water table depth was deep at our study sites (Shao et al., 2006). The measured average daily soil volumetric water content at the upper boundary was converted to matric potential by inverting the van Genuchten equation (van Genuchten, 1980):

$$\theta = \theta_r + (\theta_s - \theta_r)\left[1 + (\alpha \theta)^{n}\right]^{-m}$$  

where \(\theta\) is the soil volumetric water content (cm\(^3\) cm\(^{-3}\)); \(\theta_r\) is the residual water content (cm\(^3\) cm\(^{-3}\)); \(\theta_s\) is the saturated water content (cm\(^3\) cm\(^{-3}\)); \(\alpha\) and \(n\) are shape parameters estimated from the soil water retention curve, \(m = 1 - 1\alpha/n\) (van Genuchten, 1980); and \(b\) is the matric potential (cm).

ROSETTA, a pedotransfer function software package, contains a hierarchy of pedotransfer functions that can be used to predict hydraulic parameters from soil texture and related soil characterization data (Schaap et al., 2001). The most complex

<table>
<thead>
<tr>
<th>Depth (cm)</th>
<th>Soil texture</th>
<th>Sand (%)</th>
<th>Silt (%)</th>
<th>Clay (%)</th>
<th>Bulk density (g cm(^{-3}))</th>
<th>(\theta_{33}) (cm(^{3}) cm(^{-3}))</th>
<th>(\theta_{1500}) (cm(^{3}) cm(^{-3}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>loamy sand</td>
<td>85.5</td>
<td>12.1</td>
<td>2.4</td>
<td>1.50</td>
<td>0.14</td>
<td>0.08</td>
</tr>
<tr>
<td>40</td>
<td>sand</td>
<td>93.1</td>
<td>5.7</td>
<td>1.1</td>
<td>1.52</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>60</td>
<td>sand</td>
<td>93.8</td>
<td>5.2</td>
<td>1.0</td>
<td>1.54</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>80</td>
<td>sand</td>
<td>91.5</td>
<td>7.2</td>
<td>1.4</td>
<td>1.52</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>100</td>
<td>sand</td>
<td>91.0</td>
<td>7.7</td>
<td>1.2</td>
<td>1.57</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>120</td>
<td>sand</td>
<td>93.9</td>
<td>5.2</td>
<td>1.0</td>
<td>1.62</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>140</td>
<td>sand</td>
<td>90.9</td>
<td>7.6</td>
<td>1.5</td>
<td>1.60</td>
<td>0.10</td>
<td>0.04</td>
</tr>
<tr>
<td>160</td>
<td>sand</td>
<td>92.5</td>
<td>6.4</td>
<td>1.1</td>
<td>1.61</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>180</td>
<td>sand</td>
<td>93.1</td>
<td>6.1</td>
<td>0.8</td>
<td>1.62</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>200</td>
<td>sand</td>
<td>95.0</td>
<td>4.5</td>
<td>0.5</td>
<td>1.63</td>
<td>0.11</td>
<td>0.05</td>
</tr>
</tbody>
</table>
neural network model in the ROSETTA successfully predicts hydraulic parameters for the HYDRUS model based on percentages of sand, silt, and clay; bulk density; and -33 and -1500 kPa water contents (Bufon et al., 2012; Kandeleus and Šimůnek, 2010; Sallec, 2015; Skaggs et al., 2004). In our study, soil hydraulic parameters using the ROSETTA pedotransfer function were estimated from the soil particle size distribution, bulk density, and volumetric water contents at -33 and -1500 kPa (Table 1). The estimated van Genuchten–Mualem hydraulic parameters \((\theta_r, \theta_s, \alpha, n, K_s, L)\) for the different soil layers used in the HYDRUS-1D model are shown in Table 2.

### Soil Water Balance

We used a soil water balance to validate deep drainage based on the HYDRUS-1D model at the two sites. Assuming the surface runoff is negligible, the soil water balance in the vertical 200-cm soil profile was calculated as

\[
D = P + I - ET_a - \Delta S
\]

where \(D\) is the drainage output of the bottom of the column (mm); \(P\), \(I\), and \(ET_a\) are precipitation, irrigation, and actual evapotranspiration, respectively (mm); and \(\Delta S\) is the change in soil water storage (mm). Precipitation and irrigation in the croplands were determined using the records from the Linze Research Station. Soil water storage was estimated using soil moisture data in the 200-cm soil profile.

Actual evapotranspiration during the growth period was estimated by a combination of the FAO-56 crop coefficient approach and the Penman–Monteith model. The value of \(ET_a\) is calculated as

\[
ET_a = K_c ET_0
\]

where \(K_c\) is the crop coefficient, and \(ET_0\) is the reference evapotranspiration (mm), which is calculated by the Penman–Monteith equation (Allen et al., 1998). The \(K_c\) of the maize and wheat was determined based on prior field studies (Allen et al., 1998; Li and Shao, 2014; Li et al., 2009). The values of \(K_c\) in the maize field were adjusted to 0.42, 1.32, and 0.83 for the initial (\(=35\) d), mid-season (\(=75\) d), and late-season (\(=55\) d) stages, respectively. The values of \(K_c\) in the wheat field were adjusted to 0.39, 1.15, and 0.82 for the initial (\(=30\) d), mid-season (\(=75\) d), and late-season (\(=30\) d) stages, respectively. The \(ET_a\) during the non-growing period was also estimated using Eq. [3]. Where the surface is bare soil, the \(K_c\) value is quite similar to the value predicted in the initial stage of the growth period (Allen et al., 1998). The value of \(K_c\) recommended by Allen et al. (1998) and prior studies (Li and Shao, 2014; Li et al., 2009) was used in this study with a value of 0.30.

### Criteria for Model Evaluation

The RMSE and mean absolute error (MAE) provide a quantitative comparison of the goodness-of-fit between simulated and observed soil water contents (Moriasi et al., 2007). These indices were selected as the criteria for quantifying the deviation of the modeled results from the observed data:

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2}
\]

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |P_i - O_i|
\]

where \(n\) is the number of data, and \(P_i\) and \(O_i\) are the simulated and observed values of the \(i\)th observation.

### Results

#### Soil Properties and Irrigation

The topsoil is classified as loamy sand in the study area (USDA classification system), and the soil below the depth of 20 cm is relatively uniform and classified as sand. The topsoil has greater silt and clay content than the soil below the depth of 20 cm. Therefore, the topsoil has greater water holding capacity than the soil below the depth of 20 cm (Table 1).

The total irrigation amount in the maize field was 1197 mm in 2015 and 1041 mm in 2017. The total irrigation amount in the wheat field was 908 mm in 2015 and 837 mm in 2017 (Table 3). In early November, croplands were heavily irrigated with the intention to store soil moisture, a common practice in the region (Fig. 2). This water conservation strategy is thought to alleviate the “spring drought” and to promote seed emergence. The winter irrigation amounts were large at both sites and years (mean, 265 mm). However, the maize field was irrigated again in April to promote seed emergence due to low soil moisture. The spring irrigation amount averaged 146 mm (Fig. 2). The temporal variations in the

### Table 2. Estimated van Genuchten–Mualem hydraulic parameters \(†\) for soil layers used in HYDRUS-1D model drainage.

<table>
<thead>
<tr>
<th>Depth (cm)</th>
<th>(\theta_r)</th>
<th>(\theta_s)</th>
<th>(\alpha)</th>
<th>(n)</th>
<th>(K_s) (cm d(^{-1}))</th>
<th>(L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>120</td>
<td>0.03</td>
<td>0.36</td>
<td>0.06</td>
<td>1.59</td>
<td>175</td>
<td>-1.09</td>
</tr>
<tr>
<td>140</td>
<td>0.03</td>
<td>0.36</td>
<td>0.06</td>
<td>1.51</td>
<td>160</td>
<td>-1.14</td>
</tr>
<tr>
<td>160</td>
<td>0.03</td>
<td>0.36</td>
<td>0.06</td>
<td>1.60</td>
<td>171</td>
<td>-1.09</td>
</tr>
<tr>
<td>180</td>
<td>0.03</td>
<td>0.35</td>
<td>0.06</td>
<td>1.74</td>
<td>207</td>
<td>-1.01</td>
</tr>
<tr>
<td>200</td>
<td>0.03</td>
<td>0.35</td>
<td>0.05</td>
<td>1.47</td>
<td>216</td>
<td>-1.20</td>
</tr>
</tbody>
</table>

\(†\): \(\theta_r\), residual volumetric water content; \(\theta_s\), volumetric water content at saturation; \(\alpha\) and \(n\), shape parameters; \(K_s\), saturated hydraulic conductivity; \(L\), empirical coefficient related to the pore connectivity.
deep drainage flux in both sites in 2015 were quite different from the deep drainage flux in both sites in 2017 (Fig. 2). Figure 2 shows the low summer drainage with a sharp increase in winter drainage in 2015. The consecutive winter irrigation in November 2015 with a high irrigation amount produced the greater soil water content in the soil below the depth of 120 cm (Fig. 3), which caused the different deep drainage flux between the 2 yr.

Validation of the HYDRUS-1D Model

The measured and simulated soil water contents for two soil depths below the root zone at the two sites were plotted in Fig. 3. The simulated soil water contents were different from the measured ones (Fig. 3); the hydraulic parameters ($\theta_s$, $\alpha$, $n$, and $K_s$) without calibration would cause these deviations. There was only one soil moisture measurement at each site. The spatial heterogeneity of soil limited the accuracy of soil moisture measurements. Although other factors might result in the discrepancy of the simulated soil water contents from the measured ones (e.g., macropore flow, lateral flux of soil moisture), these were not considered in our study. Previous studies showed that preferential flow could affect soil moisture dynamics and groundwater recharge (Zhang et al., 2017, 2018). However, the overall simulated soil water contents in the two soil layers agreed well with the observed values, especially considering the fact that these simulations involved no calibration. The modeling approach in our study was to skip the complexities of the root and simulate the relatively simple soil water flow dynamics below the root zone.

The average RMSE and MAE values in the maize field were near 0.03 cm$^3$ cm$^{-3}$, whereas the average RMSE and MAE values in the wheat field were $\sim$0.04 and 0.03 cm$^3$ cm$^{-3}$, respectively (Table 4). Low RMSE an MAE values were compared with prior simulation studies (Min et al., 2017; Wyatt et al., 2017); results of this comparison indicate a good fit between simulated and observed soil water contents.

The comparison of deep drainage rates based on water balance and the HYDRUS-1D model at the two sites is shown in Table 5. The deep drainage rates for maize and wheat fields in 2015 were greater than those in 2017 (Table 5). This may be related to the fact that the winter irrigation amounts in both maize and wheat fields in 2015 were greater than those in 2017 (Fig. 2). The absolute difference between drainage rates estimated by soil water balance and by the HYDRUS-1D model averaged 51 mm yr$^{-1}$ (Table 5). The deep drainage rates based on the HYDRUS-1D model at the two sites were within $\pm$20% of those based on soil water balance (Table 5).

Deep Drainage Using Numerical Modeling

The annual deep drainage rates in the maize field at a depth of 2 m as estimated by HYDRUS-1D were 633 mm in 2015 and 476 mm in 2017 (Table 3). The annual deep drainage rates in the wheat field at a depth of 1.8 m as estimated by the model were 461 mm in 2015 and 303 mm in 2017 (Table 5). Therefore, the annual deep drainage averaged 468 mm, and the annual deep drainage coefficient averaged 43% in the young irrigated croplands.
The deep drainage was particularly great after winter irrigation (Fig. 2). The deep drainage coefficient in winter averaged 21% in the young irrigated croplands, indicating substantial water loss. The soil moisture was not efficiently stored in the soil profile due to the sandy soil characteristics (Table 1).

The comparison of HYDRUS-1D drainage coefficients and drainage coefficients from prior studies in the growing season is shown in Table 6. The analysis here is restricted to the growing season, which has been the focus of prior studies. The deep drainage in the maize field averaged 277 mm, and the deep drainage...
The HYDRUS-1D model has been previously used to simulate to address this deficiency, the model allows users to input values for the crop canopy development through the season for the two study years. These deep drainage coefficients in the two study sites were relatively close to the previous findings (Table 6).

**Discussion**

**Deep Drainage Estimation Using HYDRUS-1D**

The actual deep drainage rate can be estimated using methods such as soil water balance, chloride mass balance, and numerical modeling. However, each of the methods has limitations (Healy, 2010; Lin et al., 2013; Wang et al., 2016; Zhao and Zhao, 2014). In this study, we have shown that the HYDRUS-1D model driven by soil moisture data measured below the root zone could accurately simulate deep drainage under young irrigated croplands in the desert-oasis ecotone. The HYDRUS-1D model has been previously used to simulate soil water and solute transport and assess the effect of irrigation scheduling and management practices on nitrogen leaching in croplands (Ebrahimian et al., 2013; Li et al., 2015b; Tan et al., 2015). These numerical simulation method approaches have certain advantages of optimized design over conventional field experiments, allowing simulation of various situations at reduced cost and time relative to field experiments (Abbasi et al., 2004; Crevoisier et al., 2008). A strength of the widely used HYDRUS-1D model is its comprehensive treatment of the soil water and solute transport mechanisms, but a weakness of the model is its limited ability to simulate plant growth. The HYDRUS-1D model can simulate root growth, but it cannot simulate growth and development of the plant canopy. This deficiency becomes problematic in season-long simulations of agricultural systems where human management influences crop development, which in turn influences soil water flow. To address this deficiency, the model allows users to input values for the crop canopy development through the season on a daily or less frequent time step. The values to input can be estimated from field observations or, in some cases, remote sensing. However, this process introduces additional complexity and uncertainty in the simulations of deep drainage estimates. The novel simulation approach used in our study required some knowledge of soil physical properties (Table 1), but it required no information on weather, irrigation, or crop development. The measured soil moisture below the root zone was the main data needed to drive the model. Because of the depths considered, the complexities of soil freezing and thawing could also be neglected. The novel approach circumvents these problems and produces simulations with more simplicity and less uncertainty.

Uncertainty in deep drainage estimates is inevitable (Healy, 2010; Lin et al., 2013; Min et al., 2017). Uncertainty in the soil hydraulic properties in the numerical model contributes to uncertainty in estimating the deep drainage (Healy, 2010; Scanlon, 2000). Soil water flow is less sensitive to the parameter $\theta_s$, compared with other hydraulic parameters (Vrugt et al., 2001; Wyatt et al., 2017). Soil water flow is more sensitive to $\theta_s$, $\alpha$, and $K_s$, which affected the change by $\sim$ 4 to 8% in deep drainage (Min et al., 2017). Furthermore, the calculated deep drainage using the HYDRUS-1D model contains additional uncertainty because the hysteresis effect was not considered (Shao et al., 2006). Preferential flow could also exist and enhance heterogeneity in deep soil moisture values under the croplands in the desert-oasis ecotone (Zhang et al., 2017, 2018); thus, preferential flow might contribute uncertainty in deep drainage estimation. Despite these uncertainties, our simulation approach produced deep drainage rates within $\pm$20% of those from the soil water balance method.

### Deep Drainage of Young Cropland in the Desert-Oasis Ecotone

The annual deep drainage as estimated by the numerical model ranged from 303 to 633 mm (mean, 468 mm), and the annual deep drainage coefficient averaged 43% in the young cropland (Table 3). In the young cropland, the soil is generally coarse textured, with low organic matter and low fertility. Therefore, fertilizer is applied at $\sim$300 to 450 N kg ha$^{-1}$ each year to improve crop productivity (Su et al., 2010). Although the deep drainage recharges the groundwater, it also causes water resource loss and NO$_3$–N leaching in the desert-oasis region (Yang and Liu, 2010), resulting in NO$_3$–N groundwater pollution. The high rate of deep drainage in irrigated sandy soil should be considered to improve utilization of water resources in the desert-oasis region.

#### Table 4. Root mean square error and mean absolute error (MAE) for measured vs. simulated soil water content for the HYDRUS-1D simulations

<table>
<thead>
<tr>
<th>Year</th>
<th>Site</th>
<th>Depth (cm)</th>
<th>RMSE (cm$^3$ cm$^{-3}$)</th>
<th>MAE (cm$^3$ cm$^{-3}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>spring maize</td>
<td>160</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>200</td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>spring wheat</td>
<td>140</td>
<td>0.05</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>180</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>2017</td>
<td>spring maize</td>
<td>160</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>200</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>spring wheat</td>
<td>140</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>180</td>
<td>0.03</td>
<td>0.02</td>
</tr>
</tbody>
</table>

#### Table 5. Deep drainage rates based on soil water balance and the HYDRUS-1D model at the two study sites.

<table>
<thead>
<tr>
<th>Year</th>
<th>Site</th>
<th>Water balance</th>
<th>HYDRUS</th>
<th>Absolute difference</th>
<th>Relative difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>mm yr$^{-1}$</td>
<td>mm yr$^{-1}$</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td>spring maize</td>
<td>568</td>
<td>633</td>
<td>65</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>spring wheat</td>
<td>387</td>
<td>461</td>
<td>74</td>
<td>19</td>
</tr>
<tr>
<td>2017</td>
<td>spring maize</td>
<td>458</td>
<td>476</td>
<td>18</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>spring wheat</td>
<td>348</td>
<td>303</td>
<td>45</td>
<td>−13</td>
</tr>
</tbody>
</table>
In this study, the deep drainage during the maize growing season as estimated by the numerical model averaged 277 mm, and the deep drainage coefficient averaged 30% (Table 6). Zhao and Zhao (2014) reported that deep drainage during the maize growing season averaged 169 mm and a deep drainage coefficient of 22% based on the water balance method. Li et al. (2015a) found the deep drainage during the maize growing season was 340 mm and reported a deep drainage coefficient of 41% based on the HYDRUS-1D model. Yi (2015) reported deep drainage during the maize growing season of 284 mm and a deep drainage coefficient of 35% in two different soil types. Thus, simulated deep drainage rates for maize are consistent with the results from these previous studies.

The deep drainage during the wheat growing season as estimated by the numerical model averaged 198 mm, and the deep drainage coefficient averaged 32% (Table 6). Ji et al. (2007) reported a deep drainage during the wheat growing season of 365 mm and a deep drainage coefficient of 42%, according to a mathematical model based on Richard’s equation. In a study using coupled HYDRUS and WOFOST models, the deep drainage during the wheat growing season was 173 mm (deep drainage coefficient, 36%) (Zhou et al., 2012). Again, our simulated drainage rates are within the range of drainage rates reported for irrigated croplands in the desert-oasis ecotone.

Prior studies have focused on the deep drainage in the growing season (Li et al., 2015a; Yi, 2015; Zhao and Zhao, 2014; Zhou et al., 2012). However, the deep drainage loss after winter irrigation was substantial in the young croplands. The winter irrigation amount averaged 265 mm, the winter drainage averaged 56 mm, and the deep drainage coefficient in winter averaged 21% (Fig. 2). Likewise, Li et al. (2018) reported that the winter deep drainage in newly cultivated sandy cropland was 38 mm and that the deep drainage coefficient was 24% under 160 mm winter irrigation. Thus, the excessive winter irrigation amount in the young croplands does not promote water conservation. The sandy soil in the young croplands is poorly suited for soil water retention (Table 1).

Winter irrigation changes soil hydro-thermal features under the young irrigated croplands in the desert-oasis ecotone (Li et al., 2018). In this seasonally frozen region, part of the winter irrigation in the cropland is consumed by soil evaporation, and part is stored as ice in the soil due to freezing. After soil thawing in the spring, the stored water can provide improved soil moisture conditions for crop germination. Winter irrigation has proven to have a positive effect on alleviating the “spring drought” and promoting seed emergence (Li et al., 2018; Yang et al., 2016).

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In fact, after soil thawing, the maize field in this study required irrigation to promote seed emergence due to a low soil water content in April (Fig. 2). The thaw of the sandy soil is fast in the newly cultivated cropland, which also leads to less water conservation in spring (Li et al., 2018). Thus, the winter irrigation amount should be reduced, and supplementary spring irrigation should be used as needed to ensure crop germination under the young cropland in the desert-oasis ecotone.

## Conclusions

The study estimated the deep drainage rates under the young croplands using the HYDRUS-1D model based on soil moisture data in the deep vadose zone. The evaluation indices (RMSE and MAE) indicated that the change in soil water content was adequately modeled using the uncalibrated HYDRUS-1D model. The deep drainage obtained from the numerical model matched well with that obtained from soil water balance. Thus, the simplified numerical modeling approach based on deep soil moisture data could successfully estimate deep drainage under the young croplands in the desert-oasis ecotone. The annual deep drainage averaged 468 mm, and the annual deep drainage coefficient averaged 43%, whereas the winter irrigation amount averaged 265 mm, and the deep drainage coefficient averaged 21%. The high rate of deep drainage reduces water productivity and causes an increased risk of nutrient leaching into groundwater in the desert-oasis ecotone. Improper irrigation scheduling and the sandy soil type are detrimental to water conservation in the young croplands. Reducing winter irrigation appears to be a key strategy to reduce deep drainage and ensure the optimal utilization and management of irrigation water under young cropland on sandy soils in the desert-oasis ecotone.

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