

1 **A Unique Vadose Zone Model for Shallow Aquifers: the Hetao**
2 **Irrigation District, China**

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35 **Abstract**

36 Rapid population growth is increasing pressure on the world water resources. Agriculture will require crops to be
37 grown with less water. This is especially the case for the closed Yellow River basin necessitating a better
38 understanding of the fate of irrigation water in the soil. In this manuscript, we report on a field experiment and
39 develop a physically based model for the shallow groundwater in the Hetao irrigation district in Inner Mongolia, in
40 the arid middle reaches of the Yellow River. Unlike other approaches, this model recognizes that field capacity is
41 reached when the matric potential is equal to the height above the groundwater table and not by a limiting soil
42 conductivity. The field experiment was carried out in 2016 and 2017. Daily moisture contents at 5 depths in the top
43 90 cm and groundwater table depths were measured in two fields with a corn crop. The data collected were used for
44 model calibration and validation. The calibration and validation results show that the model-simulated soil moisture
45 and groundwater depth fitted well. The model can be used in areas with shallow groundwater to optimize irrigation
46 water use and minimize tailwater losses.

47 **Key words:** Hydrological model, Shallow aquifer, Equilibrium state, Soil moisture characteristic curve

48 **1 Introduction**

49 With global climate change and increasing human population, much of the world is facing substantial water shortage
50 (Alcamo et al., 2007). The water crisis has caused widespread concern among public governmental officials and
51 scientists (Guo and Shen, 2016; Oki and Kanae, 2006). Years of rapid population growth has squeezed the world
52 water resources. The available fresh water per capita decreased from 13400 m³ in 1962 to 5900 m³ in 2014 (World
53 Bank Group, 2019).

54 Water supply in China is especially stressed. When averaged over the whole country, available water per capita
55 is at the water stress threshold of 1700 m³ per year (Falkenmark, 1989; Brown and Matlock, 2011). It is even less in
56 the arid to semi-arid Yellow river basin that produces 33% of the total agricultural production in China. To
57 overcome water shortages in the Yellow river basin, crops are irrigated from surface and groundwater. This
58 irrigation has directly changed the hydrology of the basin. While, 50 years ago, the semi-arid North China Plain had
59 springs, shallow groundwater and rivers feeding the Yellow River, at the present rivers and springs have dried up
60 where groundwater is used for irrigation (Yang et al., 2015a). At the same time, in the arid Inner Mongolia, along
61 the Yellow River, the once deep groundwater is now within 3 m of the soil surface in the large irrigation projects

62 such as the Hetao irrigation district because of downward percolation of the excess irrigation water that has been
63 applied.

64 In the Yellow River basin, crop irrigation accounts for 96% of the total water use (Li et al., 2004). Due to the
65 increased demand for irrigation, the river has stopped flowing downstream for an average of 70 days per year
66 (Hinrichsen, 2002). Saving water upstream in Inner Mongolia by improved management practices mean that more
67 water will be available downstream (Gao et al., 2015). In addition, the Hetao district is suffering from salinization
68 which leads to the land degradation (Guo et al., 2018; Huang et al., 2018) . Salinization is caused by upward
69 migration of water (and salt) from shallow groundwater table that leads to salt accumulation at the surface (Ren et
70 al., 2016; Yeh and Famiglietti, 2009). Designing improved management practices to save water and decrease
71 salinization can be achieved by field trials or with the aid of computer simulation mode measuring the fluxes. Field
72 trials are time consuming, expensive and only a limited set of water management practices can be investigated.
73 Models can test many management practices; however, the modeling results are often questionable because they
74 have not been validated under local field condition and have not been validated for the future conditions. A
75 combination of field experiments together with models has the benefits of both approaches with few negative effects.

76 Central to modeling irrigation management practices under shallow groundwater conditions (such as in the
77 Yellow river basin) is simulating the soil moisture content accurately (Batalha et al., 2018, Gleeson et al., 2016;
78 Jasechko and Taylor, 2015; Venkatesh et al., 2011a) because the moisture content plays a critical role in the growth
79 of crops (Rodriguez-Iturbe, 2000), groundwater recharge (Hodnett and Bell, 1986), upward movement of water to
80 the root zone in areas (Gleeson et al., 2016; Jasechko and Taylor, 2015; Venkatesh et al., 2011a; Batalha et al.,
81 2018). The latter is unique to shallow groundwater areas where the moisture content and thus the unsaturated
82 conductivity are high and where the drying of the surface soil sets up hydraulic gradient that causes the upward
83 capillary movement from the shallow groundwater (Kahlow et al., 2005; Liu et al., 2016; Luo and Sophocleous,
84 2010; Yeh and Famiglietti, 2009). The upward moving water contains salt that is deposit in the root zone and at the
85 surface.

86 Modeling moisture contents

87 There is tendency with the ever increasing computer power, to include all processes and the highly
88 heterogeneous field conditions in hydrological models (Asher et al., 2015). In case of simulating moisture contents
89 these models become complex and often fully distributed in 3-D (Cui et al., 2017). Examples of these fully

90 developed models are HYDRUS (Šimůnek et al., 1998), SWAP (Dam et al., 1997) and MODFLOW (McDonald and
91 Harbaugh, 2003; Langevin, et al., 2017). These models have long run times when applied to scenarios simulations
92 for real world problems. In addition, calibration effort increases exponentially with the number of model parameters
93 (Rosa et al., 2012; Flint et al., 2002). This makes the use of the complex models for real time management and
94 decision support cumbersome where many model runs are needed (Cui et al., 2017).

95 To overcome the disadvantages of the full and complete models, computationally efficient surrogate models
96 have been developed to speed up the modeling process without sacrificing accuracy or detail. Surrogate models are
97 known under several names such as metamodels, reduced models, model emulators, proxy models and response
98 surfaces (e.g., Razavi et al., 2012a; Asher et al., 2015). The complex models we will call “full” or comprehensive
99 models.

100 Computational efficiency is the main reason for applying surrogate models in place of full models. Other
101 advantages of surrogate models are shortening the time needed for calibration; identifying insensitive and irrelevant
102 parameters in the full models (Young and Ratto, 2011). Most importantly, surrogate models allow investigating
103 structural model uncertainty (Matott and Rabideau, 2008). Finally, surrogate models might be able to deal better
104 with the self-organization of complex system prevalent in hydrology than the full models (Hoang et al., 2017). For
105 example, full models based on small scale physics (Kirchner, 2006) not necessarily can model the repetitive wetting
106 patterns observed in humid watersheds and for that reason. Simple surrogate models often outperform their complex
107 counterparts in predicting runoff when a perched water table is present in sloping terrains (Moges et al, 2017; Hoang
108 et al 2017).

109 Surrogate models can be classified in two categories (Todini, 2007; Asher et al., 2015): data driven and
110 physically derived. Data driven surrogates analyze relationships between the data available and physically derived
111 surrogates simplify the underlying physics or reduce numerical resolution. In recent years, most emphasis in the
112 research literature has been data driven surrogate approaches (Razavi et al. 2012a). Relatively little research has
113 been published on physically derived approaches. Despite its popularity, data-driven surrogates can be an inefficient
114 and unreliable approach to optimizing complex field situations especially when data is scarce such as in
115 groundwater systems (Razavi et al. 2012b) The physically derived surrogates overcome many of the limitations of
116 data-driven approaches and are therefore superior over data driven methods (Asher et al., 2015).

117 In the Yellow River basin various water accounting models have been developed to simulate the soil water
118 content and water fluxes (Xu, et al., 2012; Chen et al., 2014; Xue and Ren, 2017; Yang et al., 2017; Ren et al., 2019).
119 Numerical implementations are the finite element model HYDRUS-1D by Ren et al. (2016) and Luo and
120 Sophocleous (2010) and a finite difference model by Moiwo et al., (2010). Surrogate models for the North China
121 plain where the groundwater is more than 20 m deep have been published by Wang et al. (2001); Kendy et al (2003);
122 Chen et al. (2010); Ma et al. (2013); Yang et al. (2015, 2017a,b); Li et al., (2017). In these models, the matric
123 potential is ignored, and the hydraulic potential is equal to the gravity potential and thus the gradient of the hydraulic
124 potential is unity (at least when it is expressed in head units). Under these conditions the water flux becomes
125 negligible when the soil reaches field capacity at -33 KPa (equivalent to -3.3 m in head units) at what point the
126 hydraulic conductivity becomes limiting. These models are not valid for irrigation projects along the Yellow river
127 with shallow groundwater because the matric potential cannot be ignored over the short distance between the water
128 table and the surface of the soil. Since the gravity and matric potential are of the same order, the water moves either
129 down to the groundwater or up from the groundwater to the root zone depending on the matric potential at the soil
130 (Gardner 1958; Gardener et al, 1970a,b). In summary, for shallow groundwater at less than 3.3 m from the surface
131 equilibrium is reached (i.e. fluxes negligible) when hydraulic gradient is zero (i.e., matric potential and gravity
132 potential add up to constant value) and thus not when the conductivity becomes limited at a matric potential of -33
133 KPa.

134 For the irrigation perimeters with shallow groundwater in the Yellow River basin, we could find only two
135 surrogate models developed by Xue et al. (2018) and Gao et al. (2017a, b). These two models do not consider the
136 dynamics of groundwater depth and matric potential. By including these dynamics more realistic predictions of
137 moisture contents and upward flow can be obtained and would give better results when extended outside the area
138 where they are developed for (Wang and Smith, 2004). The reason is that for areas with shallow groundwater,
139 evapotranspiration sets up hydraulic gradient that causes the upward capillary water movement to sustain the
140 evapotranspiration demands and crop water use (Kahlowan et al., 2005; Liu et al., 2016; Luo and Sophocleous, 2010;
141 Yeh and Famiglietti, 2009).

142 Advantages of physically driven surrogates are particularly relevant groundwater studies where water tables are
143 simulated over entire large area as shown by Brooks et al. (2007). Despite this, Asher et al. (2015) poses that
144 physically driven methods have not been applied widely to groundwater problems and even fewer with the

145 interaction of moisture contents in the vadose zone which are key in salinization and plant growth of the many
146 cropped irrigated field in arid and semi-arid regions. In these water short areas it is extremely important to develop
147 models that show directions how to save water. The main objective of this study is, therefore, to develop a novel
148 surrogate model and validating this approach using experimental data collected in a field with shallow groundwater
149 with the ultimate goal is to save water in irrigation districts. In addition, sensitive and insensitive model parameters
150 were identified for simulating moisture content in shallow groundwater area to optimize future data collection
151 efforts. The experimental fields are located in the Hetao irrigation district, Inner Mongolia, China, where on two
152 maize fields, the moisture content and the groundwater table depth were measured over a two-year period.

153 The surrogate model developed is a one dimensional model simulating the moisture content in the root zone
154 using the groundwater depth and information of soil moisture characteristic curve. It can be easily adapted to field
155 scale by including the lateral movement of the regional groundwater. However, over short times, lateral movement
156 can be neglected in nearly level areas outside a strip of 5-100 m from the river (Saleh et al., 1989) such as deltas and
157 lakes (Dam et al., 1997; Kendy et al 2003).

158 **2 Materials and Methods**

159 **2.1 Study Area**

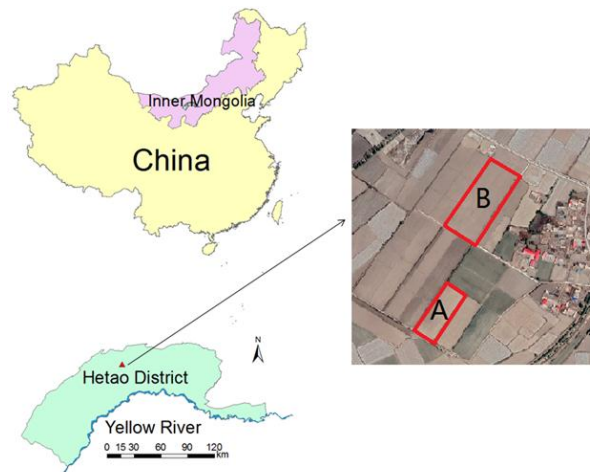
160 The Hetao Irrigation District (HID) is the third largest irrigation district of China. It covers an area of 1.12×10^6
161 ha of which half is irrigated (Xu et al., 2015). About 5 billion m^3 water are diverted from the Yellow River each year
162 (Xu et al., 2010). The primary irrigation method used is surface flood irrigation (Sun et al., 2013). The groundwater
163 table is very shallow ranging between 0.5 m to 3 m. The overall hydraulic gradient is 0.1-0.25‰ (Ren et al., 2018).
164 Soil salinization is serious, and the chemical composition of groundwater salinity mainly consists of NaCl, KCl,
165 CaSO_4 . The Hetao District has a typical arid continental climate with high evaporation and low rainfall. The average
166 annual precipitation is 180 mm and the annual potential evapotranspiration is 2225 mm (Luan et al., 2018). The soil
167 is mainly alluvial deposits with a silty loam texture. It is frozen 5 to 6 months per year from late November to the
168 middle of May. Maize and wheat are the main food crops and sunflower is the main cash crop.

169 **2.2 Field experiment and data collection**

170 The experiment was carried out in Fenzidi, Bayannur city ($41^\circ 9' \text{N}$, $107^\circ 39' \text{E}$) in the Hetao District in 2016 and
171 2017 (Fig.1). In 2016, the experiment was carried out separately in site A (about 3100 m^2) and site B (about 7000 m^2)

172 (Fig.1). In 2017, Field B was split into Fields B1 and B2 and experiments were carried out in these two fields. Field
 173 B1 was about 3400 m² and B2 about 3600 m². Experimental fields were planted both years with maize. The sowing
 174 dates were April 24, 2016 and May 13, 2017, respectively. The harvest date was October 1st in both 2016 and 2017.
 175 The plant growth stages are given in Table 1. The fields were flood irrigated three or four times during the heading
 176 and filling stages starting in late June or early July (Table 2).

177 Precipitation, air temperature, relative humidity, sunshine duration and wind speed were collected from the
 178 weather station at the experimental station. The reference evapotranspiration (ET₀) was calculated based on the
 179 FAO-Penman-Monteith equation with the daily meteorological data (Allen et al., 1998). Precipitation and ET₀
 180 during the growing season are shown in Fig. 2. The soil moisture was monitored daily in the top 90 cm using Hydra
 181 Probe Soil Sensors (Stevens Water Monitoring System Inc., Portland, OR, USA) installed in both experimental
 182 fields. Soil moisture was measured at 5 depths: 0-10 cm, 10-30 cm, 30-50 cm, 50-70 cm, and 70-90 cm. The sensors
 183 were connected to data loggers and downloaded via wireless transmission. Calibration was conducted by oven
 184 drying soil samples (Wang et al., 2018; Gao et al., 2017a). The groundwater depth was measured by piezometers
 185 (HOBO Water Level Logger-U20, Onset, Cape Cod, MA, USA) recorded at 30 min intervals.



186

187 Figure. 1 Location of the field experiment in Hetao irrigation district. The blue line is the Yellow River.

188 Table 1

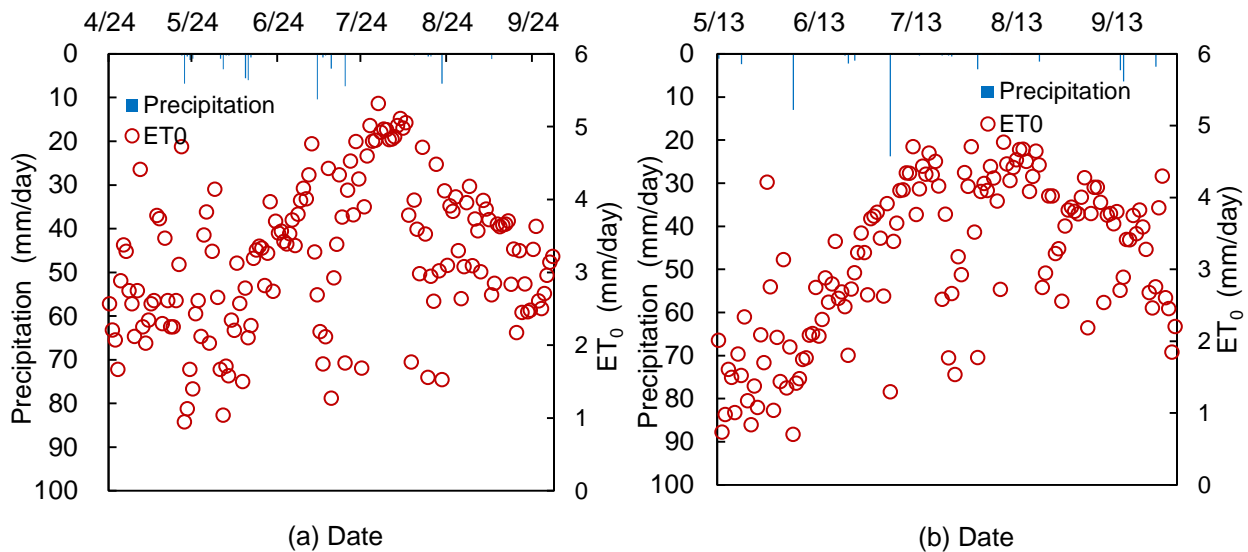
189 *Crop growth stage in 2016 and 2017 for corn growth on the Fenzidi experimental fields in the Hetao district*

Year\Growth stage	seeding	jointing	heading	filling	maturing	harvesting
2016	24-Apr	25-May	16-Jul	6-Aug	3-Sep	1-Oct
2017	13-May	11-Jun	18-Jul	8-Aug	5-Sep	1-Oct

190 Table 2

191 *Irrigation scheduling carried out at Fenzidi experimental fields in 2016 and 2017*

Year	Field	Irrigation events	Date	Irrigation depth(mm)
2016	A	First	July 13	115
		Second	July 26	86
		Third	August 8	122
	B	First	June 23	57
		Second	July 13	119
		Third	July 26	86
2017	B1	First	July 13	153
		Second	July 23	104
		Third	August 9	134
	B2	First	July 13	165
		Second	July 23	107
		Third	August 9	128



192

193 Figure. 2 Daily reference evaporation, ET₀, and precipitation during the growing season in (a) 2016 and (b) 2017

194 Soil samples were collected in rings from the same five layers where moisture contents were measured and
 195 used for determining soil physical properties including soil moisture at field capacity (θ_{fc}), soil moisture at saturation
 196 (θ_s), dry bulk density (ρ), and saturated hydraulic conductivity (K_s) (Table 3). For Fields A, B, B1 and B2, the
 197 saturated hydraulic conductivity was determined by the constant head method. Field capacity was determined at - 33

198 kPa and bulk density was determined by oven drying and dividing by the volume of the ring. Soil texture of Fields A
 199 and B were analyzed with the laser particle size analyzer (Mastersizer 2000, Malvern Instruments Ltd. United
 200 Kingdom) in the laboratory and are shown in Table 4. The American soil texture classification was used in this
 201 study. The soils vary from silty loam to silty clay loam.

202 Table 3

203 *Soil physical properties of the Fenzidi experimental fields*

Year	Field	Soil depth (cm)	θ_{fc} (cm ³ /cm ³)	θ_s (cm ³ /cm ³)	Ks (cm/d)	ρ (g/cm ³)
2016	A	0-10	0.31	0.47	11.65	1.47
		10-30	0.31	0.47	11.65	1.47
		30-50	0.32	0.51	48.71	1.36
		50-70	0.39	0.44	17.48	1.39
		70-100	0.41	0.44	40.54	1.45
	B	0-10	0.31	0.49	11.39	1.52
		10-30	0.31	0.49	11.39	1.52
		30-50	0.35	0.48	48.68	1.40
		50-70	0.40	0.49	11.06	1.42
		70-100	0.40	0.43	46.68	1.42
2017	B1	0-10	0.36	0.42	5.18	1.52
		10-30	0.36	0.46	5.18	1.52
		30-50	0.35	0.47	11.92	1.38
		50-70	0.42	0.48	4.41	1.37
		70-100	0.21	0.47	6.23	1.69
	B2	0-10	0.37	0.41	4.69	1.44
		10-30	0.37	0.45	4.69	1.44
		30-50	0.39	0.45	6.81	1.42
		50-70	0.42	0.46	10.86	1.42
		70-100	0.29	0.42	10.86	1.76

204 Note: θ_{fc} is the soil water content at -33 kPa, θ_s is the saturated soil water content, K_s is the saturated hydraulic
 205 conductivity, ρ is the bulk density.

206

207

208

209 Table 4

210 *Soil texture of Fields A and B*

Site	Depth (cm)	Soil type	Sand (%) (50-2000 μ m)	Silt (%) (2-50 μ m)	Clay (%) (0.01-2 μ m)
A	0-30	silty clay loam	5	75	2
	30-50	silty loam	22	7	8
	50-70	silty clay loam	3	8	17
	70-100	silty loam	39	57	4
B	0-30	silty loam	15	67	18
	30-50	silty loam	35	6	5
	50-70	silty clay loam	3	74	23
	70-100	silty clay loam	8	69	23

211 **2.3 The Shallow Aquifer - Vadose Zone surrogate model**

212 In developing the Shallow Aquifer - Vadose Zone surrogate model for modeling moisture contents in the
213 vadose zone, we followed the standards of good modeling practice by Jakeman et al. (2006). We made the model as
214 simple as possible, provide justification for our surrogate technique, test the surrogate model performance and
215 finally provide detail on the method to encourage discussion on the technique followed.

216 **2.3.1 Theoretical background**

217 For shallow groundwater (less than 3.3 m deep), the matric potential is a function of depth under equilibrium
218 conditions. Since the soil moisture characteristic curve for each soil is the relationship of moisture content and
219 matric potential, the moisture content is also a function of the depth of the water table under equilibrium conditions.

220 *Soil moisture characteristic curve*

221 There are several formulations describing the soil moisture characteristic curve (Bauters et al., 2000; Brooks
222 and Corey, 1964; Gupta and Larson, 1979; Haverkamp and Parlange, 1986; van Genuchten, 1980); the van
223 Genuchten and Brooks & Corey models are widely used in hydrological and soil sciences. Here, we selected the
224 Brooks and Corey model for its simplicity.

225 The Brooks-Corey model can be expressed as (Gardner et al., 1970a; Gardner et al., 1970b; Mccuen et al., 1981;
226 Williams et al., 1983).

$$S_e = \left(\frac{\varphi_m}{\varphi_b}\right)^{-\lambda} \quad \text{for } |\varphi_m| > |\varphi_b| \quad (1a)$$

$$S_e = 1 \quad \text{for } |\varphi_m| \leq |\varphi_b| \quad (1b)$$

227 in which S_e is the effective saturation, φ_b is the bubbling pressure (cm), φ_m is matric potential (cm), and λ is the pore
228 size distribution index. The effective saturation is defined as

$$S_e = \frac{\theta - \theta_d}{\theta_s - \theta_d} \quad (2)$$

229 in which θ is the volumetric moisture content, θ_s is the volumetric saturated moisture content, θ_d is the residual air
230 dry moisture content (all in cm^3/cm^3). Equation 2 can be simplified to the form by setting $\theta_d = 0$

$$S_e = \frac{\theta}{\theta_s} \quad (3)$$

231 For cases when the groundwater is close to the surface, under equilibrium conditions when the water flow is
232 negligible, (i.e., hydraulic potential is constant with depth), the matric potential can be expressed as height above
233 the water table. For our field experiment the bubbling pressure, φ_b , and the pore size distribution index, λ , in the
234 Brooks and Corey model can be obtained through a trial and error procedure by using the measured moisture
235 content and matric potential derived from the groundwater depth after an irrigation event when equilibrium state
236 was reached and sum of the gravity potential and matric potential was constant with depth.

237 **2.3.2 Parameters based on soil moisture characteristic curve**

238 The soil of the crop root zone is divided into several soil layers and each soil layer has its specific soil moisture
239 characteristic curve. After a sufficiently large irrigation and rainfall event, the moisture content is at equilibrium
240 after the drainage stops. After such an event, the soil moisture of vadose zone stays at the equilibrium moisture
241 content as long as the evapotranspiration is less than upward flux from the groundwater.

242 ***Equilibrium moisture content***

243 The equilibrium soil moisture content, θ_{equ} , in a layer can be determined by first replacing the matric potential
244 in Eq (1a) by the matric potential of the layer $\varphi_m^{z,h}$ that is dependent on the depth of the groundwater and depth of
245 the soil layer, z , e.g.

$$\varphi_m^{z,h} = h - z \quad (4)$$

246 where $\varphi_m^{z,h}$ is the matric potential under equilibrium moisture content at a depth z below the surface and h is the
 247 depth of the groundwater below the surface

$$\theta_{eq}^{z,h} = \theta_s^z \left(\frac{h-z}{\varphi_b^z} \right)^{-\lambda} \quad \text{for } |h-z| > |\varphi_b^z| \quad (5a)$$

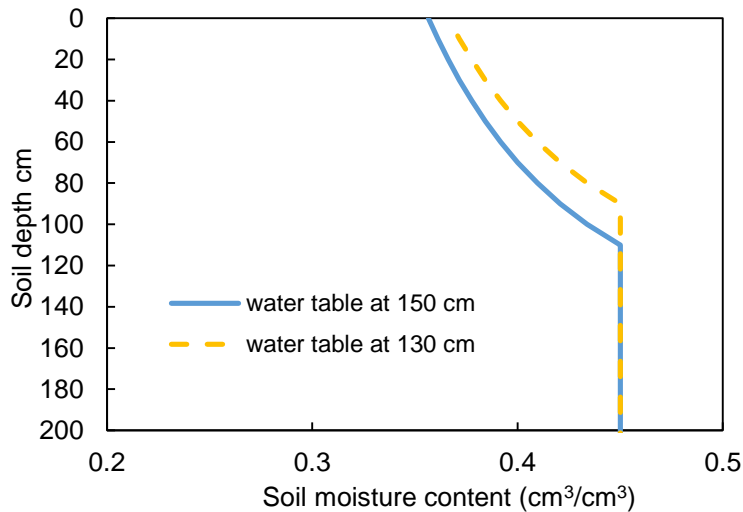
$$\theta_{eq}^{z,h} = \theta_s^z \quad \text{for } |h-z| \leq |\varphi_b^z| \quad (5b)$$

248 where $\theta_{eq}^{z,h}$ is the equilibrium soil moisture at the depth z below the surface while the groundwater depth is h . Note
 249 that the superscripts z and h indicate the dependence on the distance from the soil surface, z , and the depth, h , of the
 250 groundwater table.

251 **Drainable porosity**

252 The drainable porosity, or specific yield, is defined as the amount of water drained from the soil for a unit
 253 decrease of the groundwater table when the soil moisture is at equilibrium. It is a crucial parameter in modeling the
 254 moisture content in our case or amount of runoff for a shallow perched water table when there is rain (Brooks et al.,
 255 2007).

256 By subtracting the total moisture content at equilibrium in the profile at the initial water table depth and at the
 257 new position one unit lower, we obtain the drainable porosity. For example, the area between the orange and blue
 258 curve is the amount of water drained for a decrease in the water table from 130cm to 150cm (Fig.3).



259
 260 Figure. 3 Illustration of drainable porosity for a soil moisture characteristic curve with a bubbling pressure of 40 cm.
 261 The yellow and the blue line are the equilibrium moisture contents for the groundwater depth at 130 and 150 cm,

262 respectively. The area between the two lines represents the amount of water for the decrease of groundwater table
 263 drained from the profile when the groundwater decreases from 130 to 150 cm.

264 The total water content amount of the soil over a prescribed depth with a water table at depth h can be
 265 expressed as

$$W_{eq}^h = \sum_{j=1}^n L_j \overline{(\theta_{eq}^{z,h})}_j \quad (6)$$

266 where $\overline{\theta_{eq}^{z,h}}$ is the average equilibrium moisture content of layer j for h taken at the midpoint of the layer, n is the
 267 number of layers in the profile, L_j is the height of soil layer j . And the drainable porosity, μ^h , with the groundwater
 268 at depth h , can simply be found as

$$\mu^h = \frac{W_{eq}^{h-\Delta h} - W_{eq}^{h+\Delta h}}{2\Delta h} \quad (7)$$

269 where $\Delta h = 0.5L_j$.

270 **2.3.3 Calculating fluxes in the soil**

271 The model accounts for the downward flux due to the irrigation and rainfall, evapotranspiration by plants and
 272 soil, and upward flux from the groundwater to satisfy some or all the evapotranspiration demand by the crop and soil.
 273 There are sets of rules implemented in an Excel spreadsheet to calculate the fluxes.

274 ***Evapotranspiration***

275 1. The plant evapotranspiration was calculated in two steps. First the daily reference evapotranspiration (ET_0)
 276 was calculated by Penman-Monteith equation (Allen et al., 1998). We assumed that the moisture content
 277 was limiting therefore the plant evapotranspiration rate was obtained by multiplying the reference
 278 evapotranspiration by a crop coefficient (Allen et al., 1998; Sau et al., 2004; DeJonge et al., 2012). Values
 279 for the crop coefficients were calibrated according to the water balance in the soil and found to agree with
 280 published values for stage of crop development and soil salinity.

281 2. (a) On days without rain or irrigation, the evapotranspiration lowers the water table and the moisture
 282 content in the soil decreases due to upward movement of water to the plant roots and soil surface.

283 (b) On days with rain or irrigation, the potential evapotranspiration is subtracted from the irrigation and/or
 284 rainfall and water moves downward.

285 ***Upward flux from groundwater***

286 3. The upward flux from the groundwater, U_g^h , is either limited by the potential evapotranspiration or the
 287 maximum flux of groundwater. The maximum flux, $U_{g,max}^h$, depends on the depth of the groundwater, the
 288 type of soil moisture characteristic curve, and the condition at the surface (Gardner, 1958). These equations
 289 have an exponential form (Gardner, 1958; Yang et al., 2011; Zammouri, 2001),

$$U_{g,max}^h = \frac{a}{e^{bh} - 1} \quad \text{for } U_g^h \leq ET_p \quad (8)$$

290 where a and b are constants and ET_p is the potential evapotranspiration. The upward flux from the
 291 groundwater can be written as:

$$U_g^h = \min(ET_p, U_{g,max}^h) \quad (9)$$

292 On days without rain or irrigation, the soil moisture content is calculated by taking the difference of
 293 the equilibrium moisture content associated with the change in depth of groundwater. If in addition the
 294 upward flux is less than evapotranspiration, the difference between the upward flux and the
 295 evapotranspiration is extracted out of the root zone according to a predetermined distribution, r_j , e.g.,

$$\overline{(\theta^{z,h,t})}_j = \overline{(\theta^{z,h,t-\Delta t})}_j + \overline{(\theta_{eq}^{z,h,t})}_j - \overline{(\theta_{eq}^{z,h,t-\Delta t})}_j - \frac{r_j(K_c ET_p - U_g^h)}{L_j} \quad (10)$$

296 Where $\overline{(\theta^{z,h,t})}_j$ is the average soil moisture content at time t of layer j , $\overline{(\theta_{eq}^{z,h,t})}_j$ is the average equilibrium
 297 soil moisture content of layer j when the groundwater depth is h at time t , K_c is a reduction factor of the
 298 potential evapotranspiration for saline soil water and canopy and r_j is the root function that determines the
 299 portion of the evapotranspiration is taken up by the roots in layer j . The value z is taken at the midpoint of
 300 layer j . The time t is expressed in days and time, $t-\Delta t$, is the previous day.

301 ***The downward flux***

302 4. The rules for downward flux on days with the effective rain and/or irrigation are relatively simple. If the net
 303 flux at the surface (irrigation plus rainfall minus actual evapotranspiration) is greater than needed to bring
 304 the soil up to equilibrium moisture content, the groundwater will be recharged and the distance to soil
 305 surface decreases and the moisture content will be equal to the equilibrium moisture content at the new
 306 depth.

307 5. When the groundwater is not recharged, the following water balance will be calculated: the rainfall and the
 308 irrigation are added to first layer. This layer will be brought up to the equilibrium moisture content and the

309 remaining water fills up the next layer to the equilibrium moisture content and so on. The calculations can
 310 be expressed as follows:

$$\overline{(\theta^{z,h,t})}_j = \min \left[\overline{(\theta_{eq}^{z,h,t})}_j, \overline{(\theta^{z,h,t-\Delta t})}_j + \frac{R_{j-1}\Delta t}{L_j} \right] \quad (11)$$

311 where for $j \geq 2$, R_{j-1} is the flux from the layer above and equals

$$R_{j+1} = R_j - \frac{\left(\overline{(\theta^{z,h,t})}_j - \overline{(\theta^{z,h,t-\Delta t})}_j \right) L_j}{\Delta t} \quad (12)$$

312 For $j=1$, R_j is equal to the rainfall plus the irrigation amounts minus potential evaporation

313 **Groundwater table depth**

314 6. The groundwater in Hetao irrigation district has a small hydraulic gradient of 0.10-0.25 ‰(Ren et al., 2016).
 315 In addition, the soil varies from a silt loam to a clay loam (Table 4) that has saturated hydraulic
 316 conductivity of less than 2 m/day. This means that the lateral fluxes are small compared the vertical fluxes
 317 and can therefore neglected for the calculation of the groundwater depth. Based on this assumption, the net
 318 change in groundwater depth, Δh , can be calculated on days without rainfall or irrigation as

$$\Delta h = \frac{U_g^h}{\mu^h} \quad (13a)$$

319 and days with rain or irrigation as

$$\Delta h = -\frac{R_5}{\mu^h} \quad (13b)$$

320 where the upward flux, U_g^h , is calculated with Eq 9, the percolation of the bottom layer R_5 with Eq 12 and the
 321 drainable porosity, μ^h with Eq 7. When the groundwater is close to the surface, the drainable porosity is zero. This
 322 would make the change in groundwater infinite. Thus, we limited the maximum decrease in groundwater after the
 323 irrigation event to be 10-20 cm based on field observations.

324 **2.3.4 Model calibration and validation**

325 The soil moisture contents were measured from May 30th to September 25th in 2016 and 2017. Groundwater
 326 depth was observed from June 13th to September 26th in 2016 and 2017. For the convenience of simulation, the
 327 period of June 13th to September 25th was set as the simulation period. The model parameters were calibrated with
 328 the 2016 data and the validation with data collected in 2017 growing seasons. Soil moisture content of the top 90 cm

329 (0-10 cm, 10-30 cm, 30-50 cm, 50-70 cm, 70-90 cm) and the groundwater depth were simulated for model
 330 calibration and validation.

331 Relatively few parameters can be calibrated in the Shallow Aquifer-Vadose Zone Model. These are the crop
 332 coefficients K_c value, the two groundwater parameters and the root function. The other input data needed for model
 333 were the parameters in the Brooks and Corey equation (e.g., $\theta_s, \theta_d, \varphi_b, \lambda$.) and were obtained by fitting the equation
 334 to the soil moisture characteristic curve of each layer of the soil. The saturated moisture content was measured
 335 independently as well and agreed with values obtained from the fit. Reference evapotranspiration was calculated
 336 directly from observed meteorological data.

337 For better understanding the model fitting performance, statistical indicators were used to evaluate the
 338 hydrological model goodness-of-fit (Ritter and Muñoz-Carpena, 2013). The statistical indicators including the mean
 339 relative error (MRE) (Dawson et al., 2006), the root mean square error ($RMSE$) (Abrahart and See, 2000; Bowden et
 340 al., 2002), the Nash-Sutcliffe efficiency coefficient (NSE) (Nash and Sutcliffe, 1970), the regression coefficient (b)
 341 (Xu et al., 2015), the determination coefficient (R^2) and the regression slope (Krause et al., 2005) were used to
 342 qualify the model fitting performance during the model calibration and validation in this study. These statistical
 343 indicators can be expressed as follows:

$$344 \quad MRE = \frac{1}{N} \sum_{i=1}^N \frac{(P_i - O_i)}{O_i} * 100\% \quad (14)$$

$$345 \quad RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_i - O_i)^2} \quad (15)$$

$$346 \quad NSE = 1 - \frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2} \quad (16)$$

$$347 \quad b = \frac{\sum_{i=1}^N O_i * P_i}{\sum_{i=1}^N O_i^2} \quad (17)$$

$$348 \quad R^2 = \left[\frac{\sum_i (O_i - \bar{O})(P_i - \bar{P})}{\left[\sum_i (O_i - \bar{O}) \right]^{0.5} \left[\sum_{i=1}^N (P_i - \bar{P}) \right]^{0.5}} \right]^2 \quad (18)$$

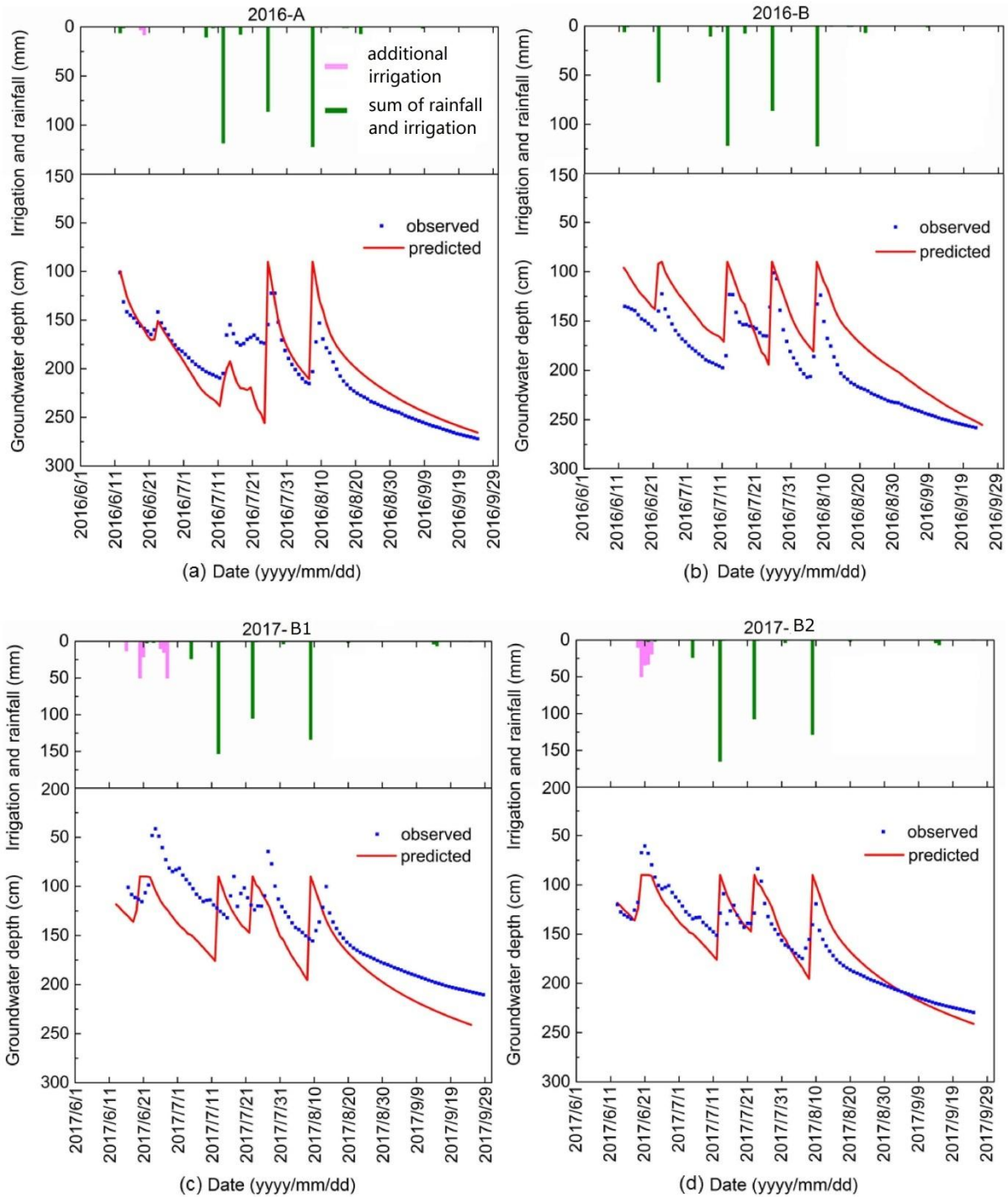
349 where N is the total number of observations, O_i and P_i are the i^{th} observed and predicted values ($i=1, 2, \dots, N$), and
350 \bar{O} and \bar{P} are the mean observed values and mean predicted values, respectively. For MRE and $RMSE$, the values
351 closest to 0 indicates good model predictions. $NSE=1.0$ means a perfect fit, and the negative NSE values indicate
352 that the mean observed value is a better predictor than the simulated value (Moriassi et al., 2007). For b and R^2 , the
353 values closest to 1 indicates good model predictions.

354 **3 Results**

355 In this section, we present first the 2016 and 2017 experimental observations of the Fenzidi experimental fields
356 in the Hetao irrigation district (Fig.1). This is followed by the calibration and validation of the Shallow Aquifer-
357 Vadose Zone Model of moisture content in each of the five layers and the groundwater table depth.

358 **3.1 Results of the field experiment**

359 The total precipitation at the experimental during growing season was 62 mm in 2016 and 67 mm in 2017. The
360 maximum daily rainfall was 23 mm in July 2017 (Fig. 2). The reference evapotranspiration varied between 1
361 mm/day to 5.5 mm/day and the total ET_0 was 517 mm and 442 mm in the growing seasons during 2016 and 2017,
362 respectively (Fig.2). Daily observation consisted of groundwater depth (blue spheres, Fig.4) and soil moisture
363 content at five soil depths up to 90 cm (blue spheres, Fig.5) and for Fields A and B in 2016 and Fields B1 and B2 in
364 2017.



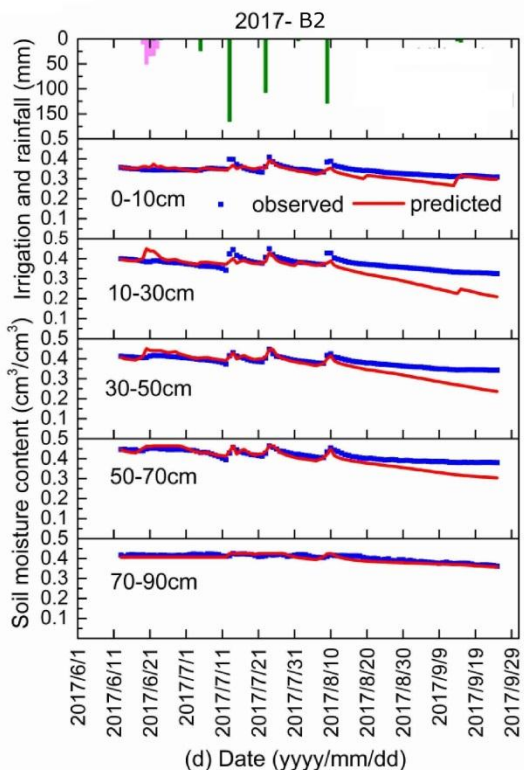
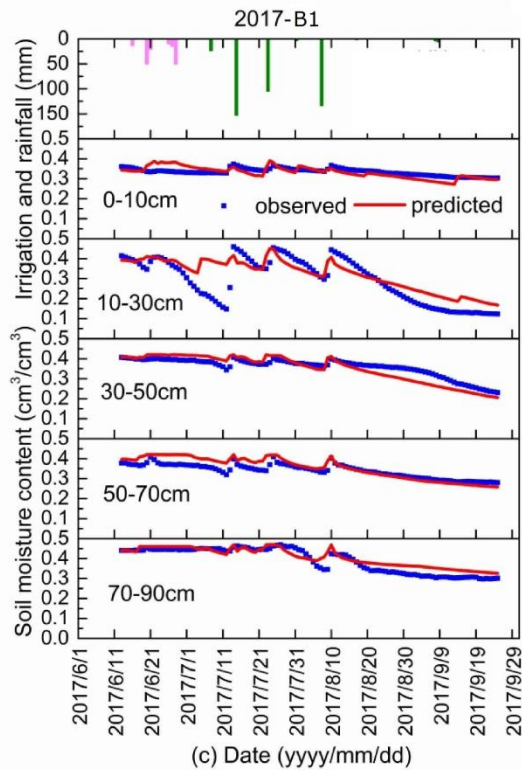
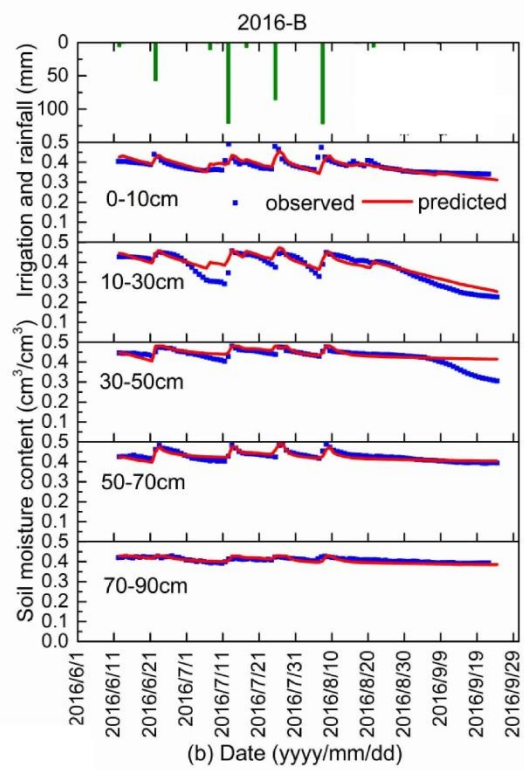
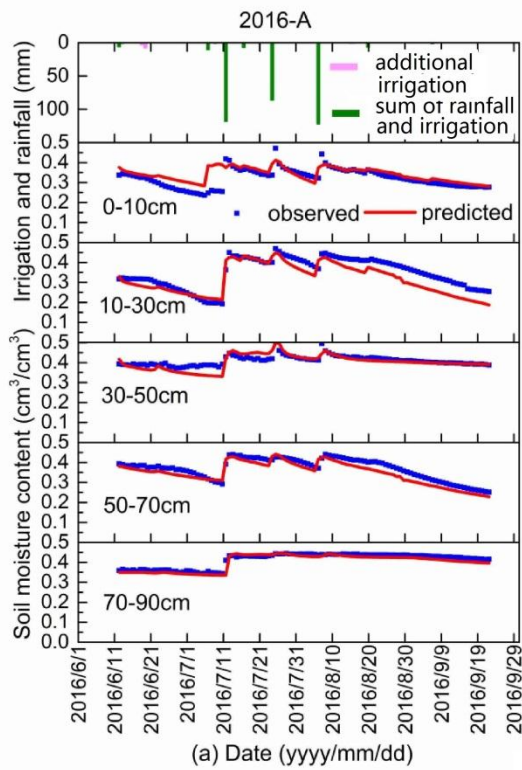
365

366 Figure.4 Simulated and observed groundwater depth during the growing period for the Fenzidi experimental fields

367 in the Hetao irrigation district: (a,b) calibration in 2016 and (c,d) validation in 2017. (Notes: Additional irrigation

368 means the irrigation recharge from the adjacent field which leads to the water table rise and was not planned).

369



370

371

372 Figure. 5 Simulated and observed soil moisture content for five soil depths during the growing period for the Fenzidi
373 experimental fields in the Hetao irrigation district: (a, b) calibration in 2016 and (c, d) validation in 2017.

374 **3.1.1 Groundwater observations**

375 In 2016, the groundwater depth was generally more than 100 cm except during the last two irrigation events on
376 Field B when it reached a depth of 72 cm for one or two days (Fig. 4). In 2017, groundwater tables were slightly
377 closer to the surface than in 2016, especially in Field B2. The minimum groundwater depth was 61 cm on June 21,
378 2017 in Field B2 after an irrigation event.

379 In general, groundwater rose during an irrigation event and then decreased slowly due to upward movement of
380 water to the plant roots to meet the transpiration demand. However, in the beginning of the growing season, we can
381 see that the water table increased without an irrigation event. This occurred on Field A on June 24, 2016 and Fields
382 B1 and B2 on June 20, 2017 (Fig. 4). This is curious and could be due to water originating from irrigation in a
383 nearby field.

384 The water table at the end of the period of observation on September 25, 2016 is approximately 2 m deep,
385 whereas on June 15, 2017, the depth decreased to around 125 cm. This is due to an irrigation application after the
386 crops were harvested to leach the salt from the surface to deeper in the profile bringing the water table up to near the
387 surface. Evapotranspiration during the winter is small but sufficient to bring the water table down. There was also a
388 rainfall event on June 5, 2017 of 13 mm (Fig. 2) before the water table was measured, increasing the water level.

389 **3.1.2 Soil Moisture**

390 Moisture contents are shown for the five layers and the two fields for 2016 and 2017 in Fig. 5. The moisture
391 contents were near saturation when irrigation water was added and subsequently decreased (Fig. 5). For example,
392 the soil moisture content changed in the 0-10 cm layer from $0.26 \text{ cm}^3/\text{cm}^3$ to $0.42 \text{ cm}^3/\text{cm}^3$ after the irrigation on
393 July 13, 2016 in Field A and then gradually decreased to $0.34 \text{ cm}^3/\text{cm}^3$. The moisture content decreased faster in the
394 10-30 cm depth than at any other depth for Fields A, B and B1 but not for Field B2. The moisture content in Field A
395 also showed a decrease at the 50-70 cm depth. For all plots, the moisture content at the 70-90 cm depth stayed nearly
396 constant and only decreased during the growing season when the water table decreased below the 150 cm depth (Fig.
397 5). In Field A, the initial moisture content when the observation started was less than saturation and then after the
398 first irrigation, remained close to the saturated moisture content.

399 It is interesting that while the soil profile was saturated (Fig. 4), the groundwater table was between 75-100 cm
400 (Fig. 5). Before equilibrium moisture content was reached the water table was likely near the surface during the
401 irrigation event. Because the drainable porosity was extremely small, even a minimum amount of evapotranspiration
402 or drainage would cause the water table to decrease to roughly the height of the capillary fringe equal to the
403 bubbling pressure, φ_b , in Eq. 5. The values of bubbling pressure are listed in Table 5.

404 3.1.3 Soil moisture characteristic curve

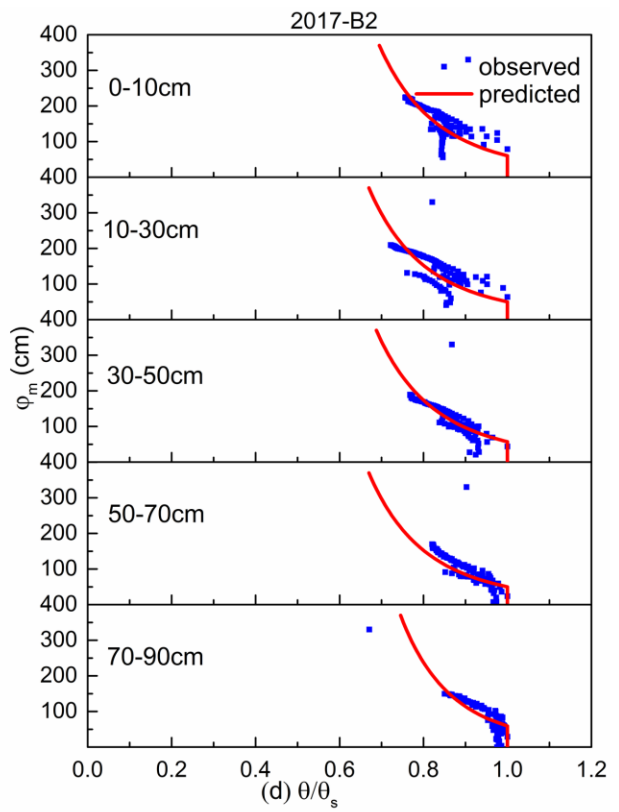
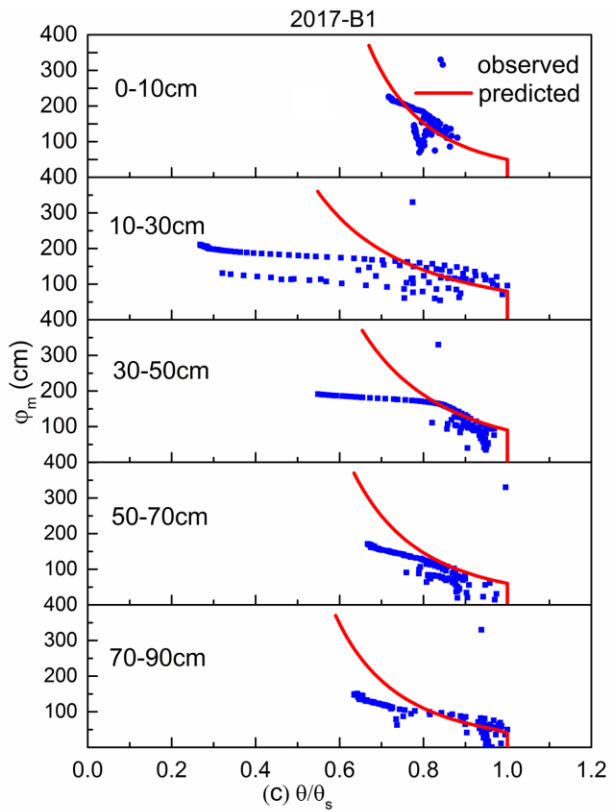
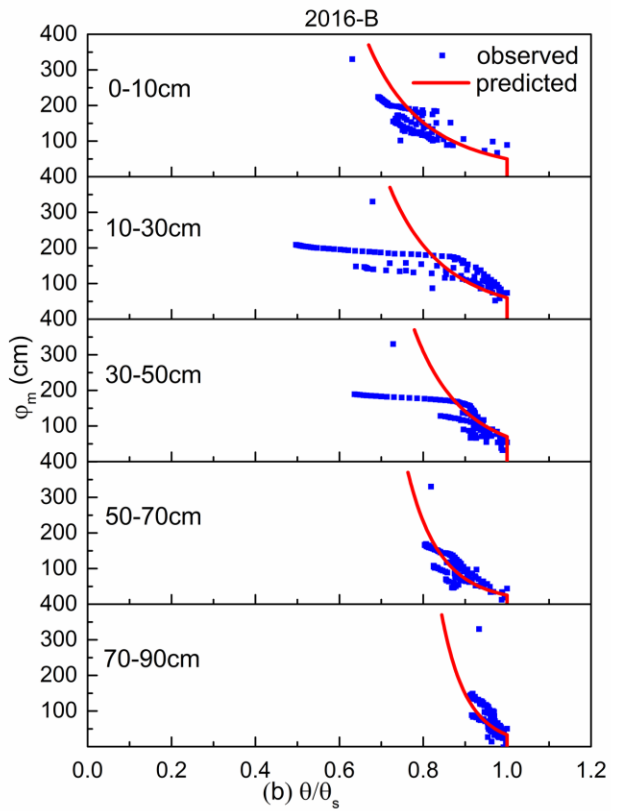
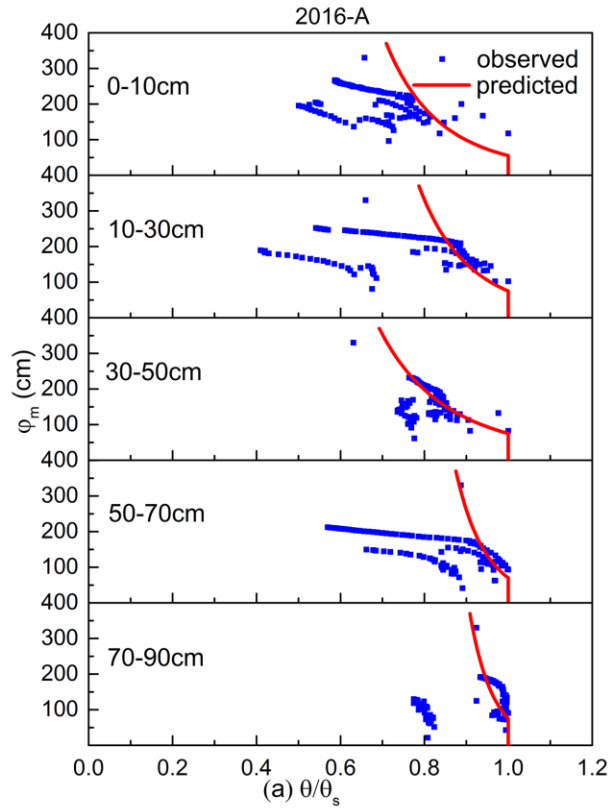
405 In 2016 and 2017, the observed reduced moisture contents were plotted versus the height above the water table
406 for the five soil layers of the two field sites in Fig. 6. These plots were used to define the soil moisture characteristic
407 curves which were of critical importance in simulating the moisture contents.

408 To define the soil moisture characteristic curve, the Brooks-Corey equation (Eq. 1) was fitted through the
409 points closest to saturation at each matric potential representing the equilibrium conditions after an irrigation event.
410 The fitted parameter values are shown in Table 5. Points to the left of the soil moisture characteristic curve are a
411 result of evapotranspiration drying out the soil when the upward movement of water was insufficient to replenish the
412 moisture content in these layers and thus matric potential and groundwater depth were not in equilibrium. In
413 addition, the few points to the right indicate the soil moisture was greater than the equilibrium moisture content.
414 Many of the outlier soil moisture contents occurred in the layer from 0-10 cm indicating that the soil was still
415 draining after a rainfall event shortly before the measurements. Thus, the soil was not at the equilibrium moisture
416 content.

417 The saturated moisture contents in Table 5 agree in general with the one measured in Table 1 but are not exact.
418 This is not a surprise as the alluvial soil deposited by the rivers with layers vary over short distances. The variation
419 within the field was also obvious from the soil's physical measurements. Fields B1 and B2 are within Field B. The
420 soil's physical properties of the various layers (Table 4) were not the same for the three sites, clearly showing the
421 variability within the field.

422 Generally, large values of pore size index coefficient λ are for sandy soils and lower values are for clay soils
423 (Bahmani and Bayram, 2018). We find this to be true for our site: for example, in Field A, the $\lambda=0.23$ corresponds to
424 a sandy layer with only 8% clay in the 30-50 cm layer (Tables 4 and 5). In the 70-90 cm layer of Field B, the $\lambda=0.07$
425 corresponds with the clay layer of 23% clay. In addition, bubbling pressure, φ_b , are greater for soils with a large

426 clay content (Bahmani and Bayram, 2018). This is demonstrated for Field A in the 10-30 cm layer where the
427 bubbling pressure of 75 cm corresponded with the clay layer of 20% clay. However, the correspondence between
428 Tables 4 and 5 is not always perfect. This is especially obvious for the layer of 70-90 cm in Field A where the values
429 in Table 5 clearly indicate that the soil has a dense clay layer; however, the soil description in Table 4 shows that the
430 soil is 39% sand. This is due to the alluvial deposition patterns with changes in soil texture over short distances as
431 mentioned before.



433 Figure.6 Soil moisture characteristic curve of the four experiment fields for the Fenzidi experimental fields. The red
 434 line is the fit with the Brooks and Corey equation.

435 Table 5

436 *Fitted Brooks and Corey parameters for the soil moisture characteristic curve*

Soil depth	Lamda(λ)				bubbling pressure (φ_b)cm				saturated moisture content (cm^3/cm^3)			
	Field	A	B	B1	B2	A	B	B1	B2	A	B	B1
0-10	0.18	0.2	0.2	0.2	55	50	50	60	0.47	0.49	0.42	0.41
10-30	0.15	0.18	0.17	0.2	75	60	70	50	0.47	0.48	0.46	0.45
30-50	0.23	0.15	0.25	0.2	75	70	50	57	0.51	0.48	0.47	0.45
50-70	0.08	0.1	0.25	0.2	70	25	30	50	0.44	0.49	0.48	0.46
70-90	0.06	0.07	0.3	0.16	75	33	45	59	0.44	0.43	0.47	0.42

437 3.2 Modeling results

438 The four parameters that can be calibrated in the Shallow Aquifer-Vadose Zone Model are the crop coefficients
 439 K_c value and the root function both related to removal of water by the atmosphere and the two groundwater
 440 parameters that determine the upward movement of water from the groundwater.

441 3.2.1 Calibration of the parameters related to moisture content

442 The first step in the calibration was to fit the K_c value from the water balance. From the moisture contents and
 443 the groundwater depth, we can calculate approximately the amount of water lost to evapotranspiration. By
 444 comparing these values to the reference evapotranspiration calculated with the Penman-Monteith equation, we found
 445 that initially during the early stages the crop coefficient was 0.3 until the filling stage and then increased to 0.7
 446 during the filling stage to the maturing stage (Table 6). These values are in accordance with the findings of Katerji et
 447 al., (2003) that salinity reduces the evapotranspiration (Katerji et al., 2003). According to the observed total salt
 448 content, the mean total salt content of experiment field in 0-100cm soil layer during crop growth period were
 449 2.29g/kg in field A, 1.79g/kg in field B, 2.33g/kg in Field B1, 20.9g/kg in Field B2, respectively.

450 The second step was calibrating the moisture content by adapting the root function indicating from what layers
 451 the water was taken up. Calibration was done manually by trial and error. We found that we could use the same root
 452 function for Fields A, B, B1, and B2 (Table 6). The calibrated soil moisture contents of the five soil layers for the
 453 two fields in general are in agreement with the measured values in 2016 (Fig 5a, b) with the coefficient of

454 determination R^2 ranging between 0.48 to 0.94 with slopes of around 1; the mean relative error (MRE) between -9.38%
 455 and 6.96% and the root mean square error ($RMSE$) varied from 0.01 to 0.04 cm^3/cm^3 for the five layers (Table 7-1).
 456 Finally, the parameters behaved physically realistically as water was extracted from shallow layers when the
 457 groundwater was close to the surface and from the deeper layers when the groundwater and the associated capillary
 458 fringe went down.

459 Table 6
 460 *Calibrated parameter values of the Vadose Zone Shallow Aquifer model*

Items	Date	Calibrated value
Crop parameter, K_c	June 13-July 14	0.3
	July 15-September 25	0.7
0-10cm	June 13-August 7	0.2
	August 8-September 3	0.1
	September 4-October 1	0.1
	June 13-August 7	0.4
	August 8-September 3	0.4
	September 4-October 1	0.4
Root function, r_j	June 13-August 7	0.3
	August 8-September 3	0.3
	September 4-October 1	0.3
	June 13-August 7	0.1
	August 8-September 3	0.2
	September 4-October 1	0.1
70-90cm	June 13-August 7	0
	August 8-September 3	0
	September 4-October 1	0.1
a	Field A	80
b		0.021
a	Field B, B1 ,B2	110
b		0.025

461 3.2.2. Validation of the parameters related to moisture content

462 The moisture contents predicted by the Shallow Aquifer-Vadose Zone Model were validated with the 2017 data
 463 on Fields B1 and B2. Although the validation statistics of the five layers were slightly worse than for calibration in

464 Table 7, the overall fit was still good as shown in Fig. 5c, d. The coefficient of determination varied between 0.39
 465 and 0.90. The *MRE* varied between -9.34% and 19.48%, and the mean *RMSE* range was from 0.01 to 0.07 cm³/cm³
 466 for the five soil layers (Table 7-2).

467 3.2.3 Calibration of the parameters related to groundwater depth

468 The final step was to calibrate the groundwater table coefficients with the 2016 data for both fields. We found
 469 that for fields not in the same location (e.g., A, B) the subsurface was sufficiently different so that the same set of
 470 parameters could not be used (Table 6). The difference between the calibrated parameters for the two fields was
 471 small (Table 6). The measured and simulated groundwater depths were in good agreement with the chosen set of
 472 parameters (Fig. 4a, b) with coefficient of determination R^2 being 0.67 for Field A and 0.85 for Field B (Table 7-1).
 473 Only from July 15 to July 25 did the observed water table on Field B decrease slower than the simulated water table.
 474 This is partly related to the fact that the properties of the soil below 90 cm were not measured, and the assumption
 475 was made the soil moisture characteristic curve below 90 cm was the same as that from 70-90 cm. Thus the
 476 drainable porosity of the soil which is very sensitive parameter might be different than what was used in the model.
 477 Another reason might be that the equation for upward movement might be too simple. Other statistical indicators
 478 show a good fit as well (Table 7-1).

479 Table 7-1

480 *Model statistics for calibration of the Shallow Aquifer model in 2016 Mean relative error, MRE; root mean square*
 481 *error, RMSE; Regression slope; Coefficient of determination, R²; Regression coefficient, b.*

Calibration (2016)								
		SWC (cm ³ /cm ³)						GWD (cm)
		0-10cm	10-30cm	30-50cm	50-70cm	70-90cm	0-90cm	
A	MRE(%)	6.96	-9.38	-1.72	-5.74	-2.31	-2.44	-16.27
	RMSE(cm ³ /cm ³ or cm)	0.04	0.04	0.02	0.03	0.01	0.03	46.52
	Regression Slope	0.51	0.94	1.34	1.01	1.05	0.50	0.50
	NSE	0.32	0.64	0.11	0.76	0.48	0.74	-0.31
	R ²	0.49	0.85	0.72	0.92	0.94	0.79	0.67
	b	1.05	0.91	0.99	0.95	0.98	0.97	0.81
B	MRE(%)	-0.69	4.21	3.83	-0.41	-0.87	1.22	1.89
	RMSE(cm ³ /cm ³ or cm)	0.02	0.03	0.03	0.01	0.01	0.02	18.28
	Regression Slope	0.93	0.72	0.37	0.76	1.14	0.76	0.85
	NSE	0.69	0.80	0.34	0.74	-0.19	0.77	0.81
	R ²	0.73	0.85	0.48	0.74	0.69	0.77	0.85
	b	0.99	1.03	1.03	0.99	0.99	1.00	1.02

482 3.2.4 Validation of the parameters related to groundwater depth

483 Since Fields B1 and B2 are in the same location as Field B, we used the same set of groundwater parameters
 484 for the three fields (Table 6). The resulting fit between observed and predicted daily groundwater depths for Fields
 485 B1 and B2 in 2017 was better than for the calibration in 2016 (Fig. 4c, d) with R^2 values of 0.84 for Field B1 and
 486 0.86 for Field B2 (Table 7-2). In both cases, the slope of the regression line was close to 1. The other statistics
 487 indicated a good fit as well (Table 7-2) with the mean relative error (*MRE*) being -0.05 for Field B1 and -0.02 for
 488 Field B2; the root mean square error (*RMSE*) is 18.02 cm for Field B1 and 16.95 cm for Field B2; the regression
 489 coefficient *b* is 0.94 and 1 for Fields B1 and B2, respectively. The general agreement between the measured and
 490 simulated groundwater depth suggests that the two parameters are adequate, and the model can be used as a tool to
 491 simulate the change of the groundwater depth.

492 Table 7-2
 493 *Model statistics for validation of the Shallow Aquifer model in 2017- Mean relative error, MRE; root mean square*
 494 *error, RMSE; Regression slope; Coefficient of determination, R²; Regression coefficient, b.*

Validation (2017)								
		SWC						GWD
		0-10cm	10-30cm	30-50cm	50-70cm	70-90cm	0-90cm	
B1	MRE(%)	-0.76	19.48	-2.84	3.60	4.83	4.86	-4.11
	RMSE(cm ³ /cm ³ or cm)	0.02	0.07	0.03	0.03	0.03	0.03	18.02
	Regression Slope	1.03	0.57	1.38	1.49	0.70	0.76	0.80
	NSE	-0.70	0.58	0.53	0.29	0.78	0.66	0.84
	R ²	0.39	0.65	0.87	0.88	0.88	0.69	0.84
	b	0.99	1.03	0.99	1.05	1.03	1.02	0.94
B2	MRE(%)	-3.67	-9.34	-6.34	-5.06	-1.75	-4.92	1.35
	RMSE(cm ³ /cm ³ or cm)	0.02	0.05	0.04	0.03	0.01	0.03	16.95
	Regression Slope	1.11	1.92	2.24	1.89	1.02	1.32	0.94
	NSE	-0.12	-3.07	-1.86	-0.81	0.63	0.02	0.85
	R ²	0.62	0.68	0.90	0.90	0.83	0.74	0.86
	b	0.96	0.92	0.95	0.96	0.98	0.96	1.00

495 **4 Discussion**

496 In this manuscript, a novel surrogate model was developed for irrigation systems where the groundwater is
 497 close to the surface. The model uses the soil moisture characteristic curve to derive the drainable porosity and to
 498 predict the moisture contents in the soil. It is based on a less often used definition of field capacity (or equilibrium
 499 moisture content as it is called in this manuscript) based on the observation that the flow becomes negligible when

500 the hydraulic gradient is zero. In other words, the system is in equilibrium when the sum of the matric potential and
501 the gravity potential is constant. Thus, when we chose the groundwater level as the reference point for the gravity
502 potential, the matric potential is equal to the height above the groundwater. This is different from other application
503 of Darcy's law where the groundwater is below 3.3 m. In these cases, groundwater movement stops when the
504 conductivity becomes negligible at -33 kPa or 3.3 m in head units. The hydraulic conductivity value above -33 kPa
505 (3.3 m in head units) does not limit the system reaching equilibrium for daily time steps. No need therefore exists to
506 measure this parameter in great detail for surrogate models. The opposite is true for the soil moisture characteristic
507 curve for determining the spatial distribution of moisture content with depth above the groundwater.

508 In general, this surrogate model simulated the soil moisture content in each soil layer well, certainly when
509 compared to other models that attempted the soil moisture contents in the Yellow River basin such as North China
510 Plain (Kendy et al., 2003) and the Hetao Irrigation District by Gao et al. (2017b) during the crop growth period. Our
511 simulation results suggest that the reduction factor of the potential evaporation for soil saline K_c and root function
512 parameters, together with the information of the soil moisture characteristic curves, can be used to adequately
513 predict the soil moisture content. To predict the groundwater depth, two additional parameters are needed for the
514 exponential function that defines the upward movement of groundwater.

515 The simulations, together with the observed data, indicated that information about the soil is very important to
516 obtain the exact moisture content in the soil. However, generalized soil moisture characteristic curves for each soil
517 type can be used in the simulation and will not result in great differences in water use by plants since percolation to
518 deeper layers was negligible and thus the only loss of water was by evapotranspiration independent of the soil
519 moisture content.

520 Finally, in the simulations we did not consider the influence of crop type and the influence of crop growth on
521 soil moisture and groundwater depth. It would be of interest to investigate in future work whether the simulations
522 would be improved by considering the dynamic crop characteristics during the growing season (Singh et al., 2018;
523 Talebizadeh et al., 2018). A mature crop model, such as the EPIC model (Williams et al., 1989) that needs
524 relatively few parameters, will certainly help to predict the crop yield but might not change the water use predictions.
525 Actually, the EPIC model already applied in Hetao irrigation district by many researchers to analyze the crop growth
526 during the crop growth period (Jia et al., 2012; Xu et al., 2015).

527 **5 Conclusion**

528 A novel surrogate vadose zone model for an irrigated area with a shallow aquifer was developed to simulate the
529 fluctuation of groundwater depth and soil moisture during the crop growth stage in the shallow groundwater district.
530 To validate and calibrate the surrogate model we carried out a two-year field experiment in the Hetao irrigation
531 district in upper Mongolia with groundwater close to the surface. Using meteorological data and the soil moisture
532 characteristic curve and upward capillary movement, the surrogate model predicted the soil water content with depth
533 and groundwater height on daily time step with acceptable accuracy during validation and was an improvement two
534 previous models applied in the Hatao district that could predict the overall water content in the root zone but not the
535 distribution with depth.

536 The surrogate modeling results show that after an irrigation event as long as the upward flux from the
537 groundwater to the root zone was greater than the plant evapotranspiration rate, the moisture contents in the vadose
538 zone could be found directly from the soil moisture characteristic curve by equating the depth to the groundwater
539 with the absolute value of the matric potential. When plant evapotranspiration rate exceeded the upward movement
540 moisture contents would be indicated by groundwater depth and was predicted by a root zone function. Another
541 finding was that the daily moisture contents were simulated without using the unsaturated hydraulic conductivity
542 function in the surrogate model. For a daily time step equilibrium (defined as the hydraulic potential being constant)
543 in moisture contents in the profile was attained so that precise unsaturated conductivity was not needed. Of course,
544 for shorter time steps, predicting the transient fluxes and groundwater the conductivity function is needed. For
545 management purposes a daily time step is acceptable.

546 Future improvement to this model will focus on coupling the EPIC model and apply it to simulate other crops
547 and other location with shallow groundwater table. The surrogate model should also be compared with a “full”
548 model, to test under what conditions the surrogate model will fall short.

549 **Data availability:** The observed data used in this study are not publicly accessible. These data have been collected
550 by personnel the College of Water Resources and Civil Engineering, China Agricultural University, with fund from
551 various cooperative sources. Anyone who would like to use these data, should contact Zhongyi Liu, Xingwang
552 Wang and Zailin Huo to obtain permission.

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