

1 **A novel regional irrigation water productivity model**
2 **coupling irrigation-drainage driven soil hydrology and**
3 **salinity dynamics, and shallow groundwater movement in**
4 **arid regions, China**

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6 Jingyuan Xue¹, Zailin Huo^{1*}, Shuai Wang¹, Chaozi Wang¹, Ian White²,
7 Isaya Kisekka³, Zhuping Sheng⁴, Guanhua Huang¹, Xu Xu¹

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10
11 ¹College of Water Resource and Civil Engineering, China Agricultural University, Beijing 100083,
12 China.

13 ²Fenner School of Environment & Society, Australian National University, Fenner Building 141
14 Canberra ACT 0200.

15 ³Univerisity of California Davis, Department of Land, Air and Water Resources & Department of
16 Biological and Agricultural Engineering

17 ⁴Texas A&M University, Agriculture Research and Extension Center, El Paso, USA

18
19 * Correspondence to: Zailin Huo (huozl@cau.edu.cn)

28 **Abstract:**

29 The temporal and spatial distribution of regional irrigation water productivity (RIWP) is crucial
30 for making agricultural related decisions, especially in arid irrigated areas with complex cropping
31 patterns. Thus, we developed a new RIWP model for an irrigated agricultural area with complex
32 cropping patterns. The model couples the irrigation and drainage driven soil water and salinity
33 dynamics and shallow groundwater movement, to quantify the temporal and spatial distributions
34 of the target hydrological and biophysical variables. We divided the study area into $1\text{ km} \times 1\text{ km}$
35 hydrological response units (HRUs). In each HRU, we considered four land-use types: sunflower
36 fields, wheat fields, maize fields and uncultivated lands (merely bare soil). And we coupled the
37 regional soil hydrological processes and groundwater flow by taking a weighted average of the
38 water exchange between unsaturated soil and groundwater under different land-use types. The
39 RIWP model was calibrated and validated using eight years of hydrological variables obtained
40 from regional observation sites in a typical arid irrigation area of North China, Hetao Irrigation
41 District. The model reasonably well simulated soil moisture and salinity, as well as groundwater
42 table depths and salinity. Overestimations of groundwater discharge were detected in calibration
43 and validation due to the assumption of well-operated condition of drainage ditches, and regional
44 evapotranspiration (ET) were reasonably estimated while ET in uncultivated area was slightly
45 underestimated in RIWP model. Sensitivity analysis indicates that soil evaporation coefficient and
46 specific yield are the key parameters for RIWP simulation. The results showed that, from 2006 to
47 2013, RIWP decreased from maize to sunflower to wheat. It was found that the maximum RIWP
48 can be reached when groundwater table depth is in the range of 2 m to 4 m, regardless of irrigation
49 water depths applied. This implies the importance of groundwater table control on RIWP. Overall,
50 our distributed RIWP model can effectively simulate the temporal and spatial distribution of
51 RIWP and provide critical water allocation suggestions for decision makers.

52 **Keywords:** Arid irrigated area, regional water productivity model, shallow groundwater, irrigation
53 process, drainage, cropping patterns

54 **1. Introduction**

55 Under the increasing food demand of growing populations worldwide, water resources is limiting
56 food production in many areas (Kijne et al., 2003; Fraiture and Wichelns, 2010). Especially, in arid
57 and semi-arid regions of the world, where irrigated agriculture accounts for about 70 to 90% of the
58 total water use (Jiang et al., 2015; Gao et al., 2017, Dubois, 2011), water deficit and related land
59 salinity are the two major limitations to agricultural production (Williams, 1999; Xue et al., 2018).
60 To maximize agricultural production, the improvement of irrigation water productivity (IWP) is
61 vital (Bessembinder et al., 2005; Surendran et al., 2016). IWP is defined as the crop yield per cubic
62 meter of irrigation water supplied, and the unit of IWP is kg/m³ (Singh et al., 2004).
63 Furthermore, by changing hydrological processes, irrigation and drainage affect water and salt
64 dynamics in crop root zone, groundwater, and, eventually, crop production (Morison et al., 2008;
65 Bouman, 2007). Specifically, in arid region, irrigation-caused deep seepage is the mainly recharge
66 of groundwater. Shallow groundwater can in turn go upward and contribute to crop water use by
67 capillary action, which means the irrigation seepage can be reused by the crop growth to improve
68 IWP. Thus, RIWP analysis requires the quantification of the complex agro-hydrological processes,
69 including soil water and salt dynamics, groundwater movement, crop water use and crop production.
70 Various methods have been used to evaluate IWP, such as field measurements (Talebnejad et al.,
71 2015; Gowing et al., 2009), remote sensing (Zwart and Bastiaanssen, 2007), and distributed
72 hydrological models (Singh, 2005; Jiang et al., 2015; Steduto et al., 2009). Field experiments have
73 been widely used to evaluate the effect of water management on IWP (Talebnejad et al., 2015;
74 Gowing et al., 2009), but field experiments are expensive and time consuming, making it unsuitable
75 for regional evaluation of IWP. Conveniently revealing temporal and spatial distributions of ET and
76 crop yields, remote sensing is commonly used to quantify regional IWP (Thenkabail and Prasad,
77 2008). However, remote sensing is looking at seeing the past IWP distribution, but cannot readily
78 predict the impacts of water management practices on IWP.

79 Recently, distributed integrated crop and hydrologic models have been widely used to simulate
80 the complex agro-hydrological processes coupled with salt dynamics and crop production (Aghdam
81 et al., 2013; Noory et al., 2011; van Dam, 2008; Vanuytrecht et al., 2007). Taking advantages of

82 geographic information systems (GIS), distributed integrated crop and hydrologic models provide
83 precise simulations of regional hydrological processes and crop growth, by incorporating the
84 heterogeneity of soil moisture, salinity and texture, groundwater table depth and salinity, and
85 cropping patterns (Amor et al., 2002; Bastiaanssen et al., 2003a; Jiang et al., 2015; Nazarifar et al.,
86 2012; Xue et al., 2017).

87 There are two types of distributed hydrologic models that are used to monitor complex regional
88 hydrological processes: numerical distributed models, such as SWAT and MODFLOW, and
89 simplified distributed models, such as FARME (Kumar and Singh, 2003) and HEC-HMS (USACE,
90 1999) based on water balance equations. Numerical, process-based models consider the entire
91 complexity and heterogeneity of regional hydrological systems. MODFLOW is commonly used for
92 groundwater dynamics simulation (Kim et al., 2008). But it is limited in well-monitored large
93 irrigation areas, due to the large number of parameters and input data required. SWAT is used to
94 simulate land surface hydrologic and crop growth processes. It relies on the digital elevation model
95 (DEM) to delineate surface water flow pathways. However, many irrigation areas are quite flat, and
96 surface water flow pathways are controlled by irrigation and drainage systems, instead of terrain
97 elevation differences.

98 Simplified distributed models often employ mass balance equations to describe the soil water and
99 salt dynamics (Sharma, 1999; Sivapalan et al., 1996), which means less input parameters, and larger
100 spatial grids and temporal steps. However, the large spatial grids poorly reflect the regional complex
101 cropping pattern heterogeneity, and the large temporal steps cannot capture daily soil water and salt
102 dynamics which is essential for crop growth simulation. SWAT alone does not describe the complex
103 interactions between groundwater and soil water, which are fundamental in arid and semi-arid areas
104 with shallow groundwater.

105 After all, there are still two big challenges for developing a distributed integrated irrigation water
106 productivity models in irrigated areas. First, the networks of irrigation canals and drainage ditches
107 cause spatial heterogeneity in irrigation, drainage, deep percolation, canal seepage and groundwater
108 table depth within the irrigation area. But previous studies have overlooked the important role of
109 the networks of irrigation canals and drainage ditches in RIWP evaluations. Second, the multi-scale
110 matching problem comes out when coupling unsaturated and saturated zone in irrigation areas with

111 complex cropping patterns, as the spatial heterogeneity of cropping patterns is much stronger than
112 that of groundwater table depth. However, most of the existing distributed hydrological models
113 simulated the hydrological processes within the same hydrological response unit (HRU) between
114 unsaturated and saturated zones independently, but overlooked the lateral exchange of groundwater
115 between adjacent HRUs.

116 Therefore, the main objectives of our study are to (1) develop a RIWP model framework coupling
117 the irrigation and drainage processes, soil water and salt dynamics, crop water and salt response
118 processes, and lateral movement of groundwater and salt; and (2) analyze the distributed RIWP of
119 the study area and find the effects of crop type, irrigation water depth applied and groundwater table
120 depth on RIWP.

121 **2. Methods**

122 We will present a four-module integrated RIWP model, the coupling between the modules and one
123 case study evaluating the model performance.

124 **2.1 Regional irrigation water productivity model**

125 General descriptions will be given for the four modules and their integration, as well as the division
126 and connections of HRUs, and boundary conditions of the model. Then, detailed descriptions will
127 be given for each of the four modules: irrigation system module, drainage system module,
128 groundwater module, and field scale IWP module.

129 **2.1.1 General descriptions**

130 A four-module integrated RIWP model was developed, to simulate the complex system including
131 water supply from irrigation open canals, field crop water consumption, groundwater drainage into
132 open ditches, and groundwater lateral flow.

133 **(1) Four modules and their integration**

134 The developed RIWP model couples an irrigation system module, a drainage system module, a
135 groundwater module and a field scale IWP evaluation module (Fig. 1). The irrigation system
136 module simulates the water flow along canals and the canal seepage to groundwater (the recharge

137 of the groundwater module), and it provides the amount of water available for field scale
138 irrigation. The drainage system module simulates the drainage to main drainage ditches from
139 groundwater, and this is the discharge of the groundwater module. The groundwater module is
140 used to simulate the groundwater lateral movement, the groundwater boundary for field scale
141 water-salt balance processes, and the groundwater level dynamics for the drainage module. In the
142 field scale IWP module, vertical movement of water and salt in soil profile is simulated, to obtain
143 the soil moisture and salinity of the crop root zone, and to calculate field scale irrigation water
144 productivity. This module provides deep percolation to the groundwater module and obtains
145 capillary rise to soil from the groundwater module. The above mentioned four modules will be
146 described comprehensively in 2.1.2 to 2.1.5.

147 **(2) Hydrological response units**

148 The irrigation area is spatially heterogeneous in terms of soil, land use, meteorology and
149 groundwater. To include the spatial heterogeneities in the simulation of regional water and salt
150 dynamics and its impact on crop growth, the irrigation district was divided into hydrological
151 response units (HRUs) (Kalcic et al., 2015). The HRU is an abstract artefact created by
152 hydrological developer and is like the smallest spatial unit of the model, which provides an efficient
153 way to discretize large watersheds where simulation at the field scale may not be computationally
154 feasible. In each HRU, soil texture and groundwater conditions are assumed to be homogeneous,
155 but different cropping patterns can exist. For example, sunflower fields, wheat fields, maize fields
156 and uncultivated lands. As the irrigation quota is different for different cropping patterns, the model
157 first runs field IWP model for each cropping pattern independently in each HRU, to obtain the soil
158 water and salt dynamics, IWP, and groundwater recharge. Then, the groundwater levels and salinity
159 of each HRU can be updated according to the area proportions of different cropping patterns in
160 each HRU. The groundwater flow is determined by pressure head gradient between adjacent HRUs.

161 **(3) Boundary conditions**

162 The upper boundary of the model is the atmospheric boundary layer above the plant canopy, which
163 determines reference ET, and precipitation. The main irrigation canals and drainage ditches directly
164 connect with groundwater and can be considered as the side boundaries in the model. With the
165 canal conveyance water loss deducted from the gross water supplied, the amount of water diverted

166 into the field can be calculated as the actual amount of irrigation. The local irrigation schedules of
167 different crops and the actual time of canal water supply are both considered to determine the actual
168 irrigation time and irrigation amounts. The lower boundary is the confining bed at the bottom of
169 phreatic layer. The phreatic layer is vitally important due to its vertical exchange with the
170 unsaturated soil zone in each HRU and its lateral exchange with adjacent HRUs to bond the whole
171 region together.

172 **2.1.2 Irrigation system module**

173 When irrigation water passes through canals, no matter lined or unlined, seepage loss occurs
174 which recharges groundwater. In a large irrigation area, there are many main, sub-main, lateral,
175 and field canals, which are categorized as the first-, second-, third-, and fourth-order canals,
176 respectively. During the water allocation period, canal seepage loss from different levels of
177 canals can be divided into two parts. One part is the seepage loss from the main and sub-main
178 canals, which are permanently filled with water and recharge directly into groundwater along the
179 route. The other part is the seepage loss from lateral and field canals, which are intermittently
180 filled with water and only recharge the groundwater units within their control area. Each HRU
181 has its corresponding groundwater unit, which is used when calculating lateral exchange of
182 groundwater between adjacent HRUs.

183 We calculated the decreasing water flow along canal, and water losses in main and sub-main canals
184 as follows (Men 2000):

$$185 \quad \sigma = \frac{A}{100Q^m} \quad (1)$$

$$186 \quad \sigma = \frac{dQ}{Qdl} \quad (2)$$

187 where σ represents the water loss coefficient per unit length per unit flow in canal (m^{-1}). A is the
188 soil permeability coefficient of canal bed ($m^{3m-1}day^{-m}$), m is the soil permeability exponent of canal
189 bed (-), and their values depend on the soil type of the canal bed (please refer to Guo (1997) for
190 the values). Q represents the daily net flow in canal (m^3day^{-1}), and dQ represents the daily flow
191 loss of the water conveyance within dl distance in canal (m^3day^{-1}).

192 Thus, Eq. (1) is equal to Eq. (2), and they can be transformed into:

193
$$Q^{m-1}dQ = Adl \quad (3)$$

194 Integrations of both sides of Eq. (3) gives:

195
$$\int_{Q_L}^{Q_g} Q^{m-1} dQ = \int_0^L A dl \quad (4)$$

196
$$Q_L = (Q_g^m - ALm)^{1/m} \quad (5)$$

197 where Q_g is the daily gross flow in the head of canal ($\text{m}^3\text{day}^{-1}$), and Q_L is the daily net flow in
 198 canal at L distance away from canal head ($\text{m}^3\text{day}^{-1}$). Thus, flow loss in water conveyance process
 199 can be calculated as follows:

200
$$Q_{Ls} = \frac{A}{100} (Q_g^m - ALm)^{(1-m)/m} \quad (6)$$

201
$$W_{ls} = Q_{Ls} / (n_1 \times A_{su}) \quad (7)$$

202 where Q_{Ls} is the daily groundwater recharge due to water conveyance loss in main and sub-main
 203 canals ($\text{m}^3\text{day}^{-1}$), W_{ls} is the daily groundwater recharge per unit area due to water conveyance loss
 204 in main and sub-main canals (mday^{-1}). n represents the total number of HRUs along selected main
 205 and sub-main canals (-), and A_{HRU} is the area of each HRU (m^2).

206 Lateral and field canals are densely distributed in the irrigated area, and they are intermittently
 207 filled with low water flow. Thus, it is assumed that seepage from these canals uniformly
 208 recharges groundwater units within their control area. The canal seepage is estimated by an
 209 empirical formula:

210
$$W_{as} = I_n * \eta_{mc} * (1 - \eta_{sbmc}) + I_n * \eta_{mc} * \eta_{sbmc} * (1 - \eta_{lc}) + I_n * \eta_{mc} * \eta_{sbmc} * \eta_{lc} * (1 - \eta_{fc}) \quad (8)$$

212 where W_{as} represents daily groundwater recharge per unit area due to water conveyance loss in
 213 lateral and field canals (mday^{-1}), and I_n is daily irrigation water depth applied per unit area (mday^{-1}). η_{mc} , η_{sbmc} , η_{lc} and η_{fc} are the utilization coefficient of main, sub-main, lateral and field canals,
 214 respectively (-).
 215

216 2.1.3 Drainage system module

217 In the drainage system module, only the groundwater draining into ditches is considered. Because
 218 the precipitation directly on ditches is negligible in arid and semi-arid area. The drainage processes
 219 are simulated based on the spatial distributions of main, sub-main, and lateral ditches, which are

220 grouped into the first-, second-, and third-order ditches, respectively. Drainage is estimated by
 221 comparing local groundwater levels and ditch bottom elevation. According to Tang et al. (2007),
 222 the groundwater drainage was calculated by:

$$223 \quad D_g = \begin{cases} \gamma_d \times (h_{db} - h_g) & ; h_{db} > h_g \\ 0 & ; h_{db} < h_g \end{cases} \quad (9)$$

224 where D_g is daily groundwater drainage per unit area (mday^{-1}). γ_d is drainage coefficient (-), which
 225 describes the groundwater table decline caused by the elevation difference between groundwater
 226 table and the streambed of the drainage ditch. And it depends on the underlying soil conductivity
 227 and the average distance between the drainage ditches. h_g represents the daily groundwater table
 228 depth (mday^{-1}), and h_{db} is the daily streambed depth of drainage ditch (mday^{-1}).

229 **2.1.4 Groundwater module**

230 For a plain irrigation area, usually groundwater levels are relatively flat on a large scale. In our
 231 model, it is assumed that groundwater lateral flow exists between one HRU and its four adjacent
 232 HRUs (Fig. 2). Using water table gradient, groundwater flow between current HRU and its adjacent
 233 HRUs can be calculated by:

$$234 \quad W_{gr} = (K \times h \times B \frac{L_{ga} - L_g}{D}) / B^2 \quad (10)$$

235 where W_{gr} is the daily groundwater inflow of the current HRU from adjacent HRUs (mday^{-1}), and
 236 K is the daily permeability coefficient of unconfined aquifers in the current HRU (mday^{-1}). h
 237 represents the thickness of unconfined aquifers, which is the difference between water table and
 238 upper confined bed and varies with water table changes (m). B is the length of groundwater unit
 239 (m) and here the value is 1km. L_{ga} and L_g represents the water table level of adjacent HRUs and
 240 the current HRU, respectively (m). D is the distance between the center of the current HRU and
 241 the centers of its adjacent HRUs (m). There are three types of groundwater boundary conditions:
 242 river head (when the boundary HRU including irrigation canal and the daily river flux equals to
 243 the daily canal flux), river flux (when the boundary HRU including drainage ditches and the water
 244 heads in ditches are assumed constant and equal to the river head) and constant flux (when the
 245 boundary HRU is mainly barren area and no irrigation is applied, thus in our study 0 flux is
 246 assumed).

247 Based on the field scale simulation, groundwater lateral exchange, canal seepage and groundwater
 248 drainage are added in the daily water and salt balance calculations of each groundwater unit at
 249 regional scale:

$$250 \quad hg_i = hg_{i-1} - (1/S_y)(Pwg_{i-1} - Gwg_{i-1} - ext_{i-1} + W_{grupi-1} + W_{grdowni-1} + W_{grlefti-1} +$$

$$251 \quad W_{grrighti-1} + W_{lsi-1} + W_{asi-1} - D_{gi-1}) \quad (11)$$

$$252 \quad SCa_i = Za \times Sa_{i-1} + W_{grupi-1} \times Sa_{upi-1} + W_{grdowni-1} \times Sa_{downi-1} + W_{grlefti-1} \times$$

$$253 \quad Sa_{lefti-1} + W_{grrighti-1} \times Sa_{righti-1} + (W_{lsi-1} + W_{asi-1}) \times Is_{i-1} - D_{gi-1} \times Sa_{i-1} +$$

$$254 \quad Psg_{i-1} - Gsg_{i-1} \quad (12)$$

255 where W_{grup} , W_{grdown} , W_{grleft} and $W_{grright}$ are the daily groundwater lateral runoff per unit area into
 256 the current groundwater unit from up and down or left and right adjacent groundwater unit,
 257 respectively (mday^{-1}). SCa is the daily soluble salt content in the saturated zone below the
 258 transmission soil profile ($\text{mg m}^{-2}\text{day}^{-1}$). Za is the thickness of the saturated zone which is the
 259 difference between the groundwater table depth and the depth that groundwater table fluctuations
 260 largely cannot reach (m). Za only affect the soluble salt concentration in the groundwater salt balance,
 261 while it has no effect on the water balance and groundwater fluctuation simulation. Sa , Sa_{up} , Sa_{down} ,
 262 Sa_{left} and Sa_{right} is the salt concentration of the current groundwater unit and its up and down or left
 263 and right adjacent groundwater units, respectively (mg m^{-3}). Is is the salt concentration of the
 264 irrigation water (mg m^{-3}). S_y represents the specific yield (-), which is the ratio of the volume of
 265 water that can be drained by gravity to the total volume of the saturated soil/aquifer. ext is the daily
 266 groundwater extraction per unit area (mday^{-1}). P_{wg} is the daily percolation water depth to
 267 groundwater from the potential root zone (mday^{-1}), and G_{wg} is the daily water depth supplied to the
 268 potential root zone from shallow groundwater due to the rising capillary action (mday^{-1}). P_{sg} and
 269 G_{sg} are the quantity of soluble salt in P_{wg} and G_{wg} , respectively ($\text{mg m}^{-2}\text{day}^{-1}$). The detailed
 270 calculations of the water and salt exchange components between unsaturated soil and groundwater,
 271 such as P_{wg} and G_{wg} , were described in our previously developed water productivity model at field
 272 scale (Xue et al., 2018).

273 **2.1.5 Field scale irrigation water productivity module**

274 Cropping patterns are complex for each HRU and sometimes HRUs include uncultivated land, forest

275 land and other non-agricultural land. In our model, with high resolution land use map, different
276 cropping patterns can be separated to simulate soil water and salt processes, and the responses of
277 ET and crop yields to water and salt content of root zone. Here, we employed our previously
278 developed field IWP model to simulate field water, salt, ET and crop yield under shallow
279 groundwater condition (Xue et al., 2018). The soil profile is vertically divided into four soil zones:
280 the current root zone, the potential root zone, the transmission zone, and the saturated zone. In each
281 HRU, the soil water and salt balance processes, and water productivity are independently simulated
282 for each cropping pattern under its corresponding groundwater unit condition. For uncultivated
283 lands, only water and salt balance are simulated, and its IWP is 0. Then, the water and salt exchange
284 between unsaturated soil and groundwater of different cropping patterns are weighted averaged by
285 area proportion. Finally, the weighted averages are used to update daily groundwater table and
286 salinity (Fig. 3).

287 **2.2 Modules coupling and calculating flowchart**

288 The simulation was by daily temporal step and by HRU spatial step. The irrigation system module
289 simulates the canal seepage to groundwater and the field irrigation water amount. And the canal
290 seepage to groundwater is the recharge of the groundwater module, while the field irrigation water
291 amount is the input of the field IWP module. The drainage system module simulates the
292 groundwater drainage to drainage ditches, which is the discharge of the groundwater module. The
293 groundwater module is used to simulate the groundwater table depth, which is the input of the field
294 IWP module and also the input of the drainage module. In the field scale IWP module, the deep
295 percolation to groundwater under different cropping patterns are simulated independently and their
296 weighted average is the recharge of the groundwater module. The salt exchange is simulated
297 together with water exchange. The groundwater module is used to simulate the groundwater lateral
298 movement between the current HRU and its adjacent HRUs to update the groundwater level at next
299 time step. By coupling the irrigation system module, drainage system module and groundwater
300 module with the field IWP model, this RIWP model simulates the temporal and spatial distribution
301 of IWP in the whole irrigation area from the beginning to the end of the growing season.

302 The model was implemented in a combination of ArcGIS, MATLAB, and Microsoft Excel (Fig. 4).

303 The HRUs was created in ArcGIS as fishnet, with each grid numbered. In MATLAB, the HRUs
304 were represented by a matrix and the daily time step was represented by a vector. At each time step,
305 all the HRUs were traversed by a nested loop. Then the updated information for the current time
306 step was used to calculate the next time step. Microsoft Excel stored ArcGIS vector layer and its
307 attribute data for MATLAB modeling, and also stored MATLAB output results for ArcGIS analysis
308 and visualization.

309 Considering the high spatial heterogeneity, meteorological data need to be collected from all the
310 weather stations within or close to the study area. Distribution of soil physical properties, moisture
311 and salinity in unsaturated soil, groundwater table depth and salinity, need to be collected from
312 many observation sites, which are uniformly or randomly spread over the study area. Then, each
313 data set can be interpolated in ArcGIS by inverse distance weight to obtain a spatial distribution
314 vector layer. For each layer, the average value in each HRU are calculated by ArcGIS using
315 geometric division statistics. The vector layer of irrigation control zones and the vector layer of
316 drainage control zones is respectively overlaid with the HRU division layer in ArcGIS, to obtain the
317 HRU numbers controlled by each irrigation control zone and each drainage control zone. The HRU
318 numbers controlled by the same zone are stored in the same matrix for batch simulation in MATLAB.
319 In MATLAB, soil water and salt balances and field scale IWP for main crops are simulated
320 simultaneously for each HRU; whereas, groundwater lateral exchange are simulated between
321 adjacent HRUs. At the end of the model simulation, soil moisture and salinity, groundwater table
322 depth and salinity, ET, crop yield and IWP for different land use types in each HRU can be obtained.
323 Then, the area proportion weighted average in each HRU can be imported into ArcGIS to visualize
324 the spatial distribution.

325 **2.3 Model evaluation**

326 We will provide a case study using the above developed new RIWP model, to test its applicability,
327 and to provide sensitivity analysis of the parameters.

328 **2.3.1 Description of study area and data**

329 As a typical sub-district of the Hetao Irrigation District, the Jiefangzha Irrigation District (JFID) is

330 a typical arid irrigated area with shallow groundwater, resulted from its arid-continental climate,
331 over years of flood irrigation, and poor drainage systems (Fig. 5). Located in the Hetao Plain, the
332 JFID is very flat with an average slope of 0.02% from southeast to northwest (Xu et al., 2011). The
333 mean annual precipitation is only 155 mm, of which 70% occurs between July to September; while
334 the mean annual potential evaporation is 1938 mm. The mean annual temperature is 7°C, with the
335 lowest and highest monthly average being -10.1°C and 23.8°C in January and July, respectively.
336 The JFID covers an area of 0.22 Mha, of which 66% is irrigated farmland area. Wheat, maize and
337 sunflower as the main crops in this region, taking up more than 90% of the irrigated farmland area.
338 The 12×10^8 m³ annual irrigation water is diverted from the Yellow River. Due to the poor
339 maintenance of drainage ditches, it is quite common in this area to have poor drainage situations.
340 Therefore, the annual average groundwater table depth ranges from 1.5 to 3.0 m during the crop
341 growing season. Soils in the JFID are spatially heterogeneous and primarily composed of silt loam
342 in the northern region and sandy loam in the southern region. Shallow groundwater table and strong
343 evaporation makes soil salinization a very serious problem in this area, which is becoming the main
344 constraint of crop production.

345 An irrigation and drainage network include four main irrigation canals, sixteen sub-main irrigation
346 canals, five main drainage ditches, and twelve sub-main drainage ditches are controlling the water
347 movement in the JFID (Fig. 5). The streambed depths of the regional main, sub-main and lateral
348 ditches were collected by a regional survey in 2016. Daily water flow data in the main and sub-main
349 irrigation canals and monthly data of the five main drainage ditches were obtained from the local
350 Irrigation Administration Bureau. A total of 55 groundwater observation wells are installed in the
351 JFID (Fig. 5). Groundwater level was measured on the 1st, 6th, 11th, 16th, 21th and 26th of each month,
352 and groundwater salinity was measured 3 times each month. Near the groundwater observation wells,
353 soil moisture was measured four times, and soil electrical conductivity was measured once before
354 wheat sowing and once before autumn irrigation. Due to the spatially homogeneous climate in JFID,
355 daily meteorological data (air temperature, humidity, wind speed and precipitation) was obtained
356 from Hangjinghouqi weather station for the calculation of regional reference ET.

357 HJ-1A, HJ-1B and Landsat NDVI images with 30 m resolution during the period of 2006-2013 were
358 downloaded from the official website of China Centre for Resources Satellite Data and Application

359 (2013) and USGS (2013), to determine the annual cropping pattern distributions. Due to the lack of
360 measured ET, the ET estimated by SEBAL model using MODIS images from NASA (2013) was
361 used as a reference to compare with simulated ET values (Bastiaanssen et al., 2003b).

362 **2.3.2 Parameterization of distributed RIWP model**

363 The JFID was divided into 2485 1km×1km HRUs (Fig. S1a in the supplementary material). In
364 terms of boundary conditions, the upper Quaternary 4 aquifer layer was regarded as the phreatic
365 layer in the model. It was modeled as an aquitard with loamy soil. From north to south, the thickness
366 of aquifer in JFID varies from 2 to 20m with an average of 7.4m (Bai et al., 2008). Thus, the initial
367 value of the average thickness of unconfined aquifer is set as 7.4m. The water level contour maps
368 of JFID during 1997-2002 by Bai (200) were used to determine the direction of water flow near the
369 groundwater boundary. Based on the topography conditions, land-use types, locations of main
370 canals and ditches, and directions of water flow, the regional phreatic layer was divided into 5 zones
371 with river, drainage and impervious boundary conditions (Fig. S1b).

372 The JFID was divided into four irrigation control sections and five drainage control sections, each
373 section was controlled by one main irrigation canal or one main drainage ditch. These sections were
374 further divided into 48 irrigation control sub-areas and 17 drainage control sub-areas, each sub-area
375 was controlled by one sub-main irrigation canal or one sub-main drainage ditch (Fig. S2). The
376 sunflower fields, wheat fields, maize fields and uncultivated lands are the four cropping patterns,
377 i.e., land-use types, in the RIWP model. In many other researches about distributed hydrological
378 models, when considering the applied irrigation schedule the sowing and irrigations of a particular
379 crop were just set as on the same day over the whole study area, which may be a simplification of
380 actual conditions (Singh, 2005). In our study, the irrigation time and irrigation water amount of each
381 HRU were co-determined by both the local irrigation schedule of the three main crops, and the
382 actual water amount flowing into the fields.

383 The simulation period was from April 1st to September 20th, which covers the growing seasons of
384 all the three main crops. The initial crop parameters were set as the default values suggested for
385 sunflower, wheat, and maize by Allen et al. (1998). The empirical values of regional canal
386 utilization and ditch drainage coefficient were obtained from Jiefangzha administration.

387 2.3.3 Model calibration and validation

388 To comprehensively evaluate the accuracy and reliability of the model, the data in years 2010-2013
 389 and in years 2006-2009 was respectively used as calibration and validation dataset. The daily
 390 measured soil moisture content of crop root zone (θ), electrical conductivity of soil water (EC),
 391 groundwater table depth (h_g) and groundwater salinity, were calibrated with measured data from
 392 the 22 soil water and salt observation sites and 55 groundwater observation sites (Fig. 5), which
 393 were mentioned in section 2.3.1. The RIWP simulated regional ET for each HRU was calibrated
 394 by the remote sensing based ET images obtained once per 8 days. The regional drainage processes
 395 was calibrated by the monthly groundwater drainage data from main ditches, in which the
 396 simulated drainage of each main ditch was the sum of drainage of its controlling HRUs. Overall,
 397 the soil hydraulic parameters, the crop water productivity related coefficient, and the canal
 398 conveyance and ditch drainage parameters were all calibrated with observed data in years 2010-
 399 2013, and then validated with observed data in years 2006-2009.

400 To quantify the model performance, the root mean square error (RMSE), the Nash and Sutcliffe
 401 model efficiency (NSE) and the coefficient of determination (R^2) were used as the indicators.
 402 RMSE was used to measure the deviation of simulated values from the measured ones, NSE was
 403 commonly used to verify the credibility of the hydrological model, and R^2 represented the degree
 404 of linear correlation. The indicators were calculated as follows:

$$405 \quad RMSE = \left[\frac{\sum_{i=1}^n (Output_s - Output_o)^2}{n} \right]^{0.5} \quad (13)$$

$$406 \quad NSE = 1 - \frac{\sum_{i=1}^n (Output_s - Output_o)^2}{\sum_{i=1}^n (Output_o - Output_m)^2} \quad (14)$$

$$407 \quad R^2 = 1 - \frac{\sum_{i=1}^n (Output_o - \overline{Output_o})(Output_s - \overline{Output_s})}{\sqrt{\sum_{i=1}^n (Output_o - \overline{Output_o})^2} \sqrt{\sum_{i=1}^n (Output_s - \overline{Output_s})^2}} \quad (15)$$

408 where n is the number of simulations; $Output_s$ and $Output_o$ are simulated and observed values of
 409 model outputs, respectively; $\overline{Output_s}$ and $\overline{Output_o}$ are the average values of simulated and
 410 observed model outputs, respectively. The $RMSE$ indicates a perfect match between observation
 411 and simulation when it equals 0, and increasing $RMSE$ values indicate an increasingly poor match.
 412 Singh et al. (2005) stated that $RMSE$ values less than 50% of the standard deviation of the

413 observed data could be considered low enough as an indicator of a good model prediction.
414 Ranging between $-\infty$ and 1, the NSE indicates a perfect match between observed and predicted
415 values when it equals to 1. Values between 0 and 1 are generally considered as acceptable levels
416 of performance, whereas values less than 0.0 indicate that the simulation is worse than taking an
417 average of observation, which indicates unacceptable performance. The R^2 ranging between 0 and
418 1 describes the proportion of the variance in the observed data, in which higher values indicating
419 less error variance. Typically, $R^2 > 0.5$ is considered acceptable (Santhi et al., 2001).

420 **2.3.4 Global sensitivity analysis**

421 To find the key parameters significantly impacting the model output, a global sensitivity analysis
422 was conducted. The analysis related the changes in three output variables—RIWP, groundwater
423 table depth and groundwater salinity—to eight parameters in the RIWP model. The Latin Hypercube
424 Sampling (LHS) (please see Mckay, 1979; Muleta et al., 2005; Wang et al., 2008 for detailed
425 descriptions of the sampling method), a typical sampling method for sensitivity and uncertainty
426 analysis, was used to sample the parameter space. According to Dai (2011), to ensure that the test
427 points were evenly distributed in space and to guarantee the accuracy of the test, the test number
428 was set as 20, more than double of the parameter number which was 8. For uniform distributions,
429 the parameter range was subdivided into 20 equal intervals. Each interval was sampled only once to
430 generate random values of the possible parameter sets. The possible parameter value ranges referred
431 to the local measurements, survey data and relevant research papers. Additionally, considering the
432 spatial heterogeneity of the three output variables, 22 evenly distributed groundwater observation
433 sites in JFID were selected for the global sensitivity analysis. Based on the LHS method, 20 groups
434 of parameter combinations were obtained and the simulation was run for 20 times. Finally, the
435 sensitivity of the three output variables to the eight parameters were determined in SPSS Statistics.
436 The absolute values of the obtained Standardized Regression Coefficients (SRCs) quantified the
437 significance of each parameter to each output variable (Table 1) (Cheng et al., 2018; Cannavó,
438 2012). And the plus or minus sign of the SRCs indicated the positive or negative correlations
439 between the corresponding parameter and output variable pairs.

440 3. Results and Discussion

441 3.1 Model performance

442 Good agreements were obtained by RIWP model in simulating IWP and hydrological components
443 during the calibration and validation periods. Table 2 tabulated the calibrated parameters describing
444 crop growth and water usage, and Table 3 tabulated the possible variation ranges and calibrated
445 values of the parameters describing soil hydraulic characteristics and irrigation and drainage system.
446 The agreement between the observed and simulated soil moisture content in crop root zone both in
447 calibration (Fig. 6a, $RMSE=2.867 \text{ cm}^3 \text{ cm}^{-3}$, $NSE=0.330$, $R^2=0.502$) and validation (Fig. 6b,
448 $RMSE=2.989 \text{ cm}^3 \text{ cm}^{-3}$, $NSE=0.232$, $R^2=0.548$) indicates the reasonable performance of the RIWP
449 model. The good performance of the RIWP model was also indicated by the simulation of the soil
450 salt content both in calibration (Fig. 6c, $RMSE=1.108 \text{ dS m}^{-1}$, $NSE=0.612$, $R^2=0.657$) and validation
451 (Fig. 6d, $RMSE=1.205 \text{ dS m}^{-1}$, $NSE=0.525$, $R^2=0.590$). The simulated and observed groundwater
452 table depth (Fig. 6e, $RMSE=0.786\text{m}$, $NSE=0.424$ and $R^2=0.509$ in calibration; Fig. 6f,
453 $RMSE=0.667\text{m}$, $NSE=0.637$ and $R^2=0.504$ in validation) and groundwater salinity (Fig. 6g,
454 $RMSE<10\%$, $NSE=0.813$ and $R^2=0.815$ in calibration; Fig. 6h, $RMSE<10\%$, $NSE=0.604$ and
455 $R^2=0.730$ in validation) at 55 observation sites are in good agreement as well.

456 The model did not perform very well on simulating groundwater drainage. The overestimated
457 drainage (Fig. 6i-j) was due to the different operating conditions of the drainage ditches of the
458 different order. Remember that we classified the main, sub-main and lateral drainage ditches into
459 the first-, second- and third-order ditches, respectively. In the model, for each year, we adopt same
460 drainage coefficient for all the ditches of the different orders, assuming a well operated condition.
461 However, the actual operating conditions of the ditches of the different orders cannot be the same,
462 resulting in the simulation discrepancy.

463 The ET simulated by the RIWP model (ET_{IWP}) and the ET estimated by the SEBAL model using
464 MODIS images (ET_{RS}) agrees well both in calibration ($RMSE=1.918\text{mm}$, $NSE=0.274$ and $R^2 =$
465 0.561) and in validation ($RMSE=2.132\text{mm}$, $NSE = 0.189$ and $R^2 = 0.498$) (Fig. 6l). Furthermore, the
466 comparison of the spatial distribution of cumulative ET_{IWP} and ET_{RS} during crop growth season
467 showed that ET_{IWP} was lower than ET_{RS} in uncultivated area, while they agreed well in farmland
468 (Fig. S3). The uncultivated area, merely bare soil, accounted for about 34% of the JFID, and the

469 ET_{IWP} of uncultivated area was merely soil evaporation. This, resulted in the underestimation of
470 actual ET in uncultivated area compared to the ET acquired by remote sensing images, which was
471 consistent with previous studies (Singh, 2005; Tian et al., 2015). Besides, the cumulative ET_{RS} was
472 taken by the 8 times of daily ET on satellite acquisition date, thus using the non-representative ET_{RS}
473 above the average daily value may also result in the underestimation of ET_{IWP} .

474 To test the model performances under different cropping patterns, one representative site was
475 selected for each cropping pattern to compare the observed and simulated time series of groundwater
476 table depth (Fig.7). Results indicated that the model can adequately capture the groundwater
477 dynamics at the four representative sites. Occasionally, the simulated groundwater table depth
478 declines fast, while the observed value rises. This is most likely due to the fact that we ignored the
479 time lag between groundwater recharge from soil and deep percolation. In the uncultivated area
480 (Fig.7a), simulated groundwater table level presented a slower and more flat decreasing trend than
481 measured value. By assuming a completely non-vegetation coverage condition of uncultivated area
482 while it is not actually the case, estimated groundwater evapotranspiration driven by capillarity will
483 become smaller than its actual value, in which small vegetation will transpires amounts of water
484 from soil and soil moisture is relatively low thus groundwater evapotranspiration is higher.

485 **3.2 Global sensitivity analysis**

486 Recall that the global sensitivity analysis was to determine the sensitivity of the three output
487 variables to eight parameters. The three output variables were RIWP, groundwater table depth, and
488 groundwater salinity; while, the eight parameters were those parameters describing soil hydraulic
489 characteristics and irrigation and drainage system, tabulated in Table 3. Specific yield (S_y), followed
490 by soil evaporation coefficient (K_e), are the two key parameters influencing the RIWP (Fig. 8a). The
491 specific yield indicated the readily available soil moisture released to crop root zone from shallow
492 aquifer under capillary action for crop consumption. Thus, its significant positive influence on
493 RIWP was explained. The soil evaporation coefficient indicated the proportion of water that
494 transferred into the atmosphere but was not used by crops. Therefore, its significant negative impact
495 on RIWP was expected. We concluded that for shallow groundwater buried area like JFID,
496 sometimes the effect of groundwater contribution on IWP would be greater than that of irrigation

497 water depth applied. Applying lots of shallow irrigation to the crops may reduce the deep percolation
498 and decrease the non-beneficial water use in evaporation. Applying fewer and deeper irrigation
499 water applied will result in deeper percolation meanwhile greater groundwater contribution to
500 beneficial crop water use. Thus, compared with lots of shallow irrigation applied, applying fewer
501 deeper irrigation schedule may have greater affect on IWP in arid regions with shallow groundwater.
502 And for both groundwater table depth (Fig. 8b) and groundwater salinity (Fig. 8c), specific yield
503 was the only key parameter. Canal seepage was expected to cause the variation of groundwater table
504 depth around the canal at the local scale. However, the results indicated that the variation of
505 groundwater table depth would be more susceptible to the local groundwater properties, i.e., specific
506 yield, than to canal seepage at the regional scale. We speculate that the lateral groundwater
507 movement might compensate the variation of groundwater table depth caused by the canal seepage.
508 Salt moves with water. Thus, the variation of groundwater salinity was also dominated by the
509 specific yield. Due to the high sensitivity of IWP, groundwater table depth and salinity to the specific
510 yield, it is highly recommended to use spatially variable values of specific yield rather than a
511 constant one as a model input if it is available, which could greatly enhance the evaluation accuracy
512 of the RIWP model. Also, it is indicated that the permeability coefficient of unconfined aquifers (K)
513 did not significantly affect the IWP, groundwater table depth and salinity. Due to the lack of
514 measurement data in our study, we adopted a unified K value for the whole study area, which also
515 make the model simulations reasonable for their insensitive to this parameter.

516 **3.3 Regional irrigation water productivity**

517 **3.3.1 Spatial distribution of irrigation water productivity**

518 Validated by the measured soil moisture and salinity, groundwater table depth and salinity, drainage
519 water depth and ET, especially, the year 2006-2013 time series of groundwater table depth under
520 the four cropping patterns, the developed RIWP model can be used to estimate the spatial
521 distribution of IWP for the three main crops over the period of 2006-2013 (Fig. 9). Note that these
522 IWP values were based on the simulated water balance and crop yields of individual HRU, which
523 may deviate to a certain extent from the real values. It can still represent the utilization of water

524 resources at the regional scale. We could see there are “red HRUs” in Figure 9 changing with time
525 and space due to different irrigation water depth applied under different groundwater conditions.
526 Even different crop species can result in big difference in IWP. As we mentioned before, the spatial
527 distribution of these three crops is very complex in JFID and field plot is small, thus we use remote
528 sensing data to obtain cropping pattern map with resolution of 30m*30m. Every HRU has these
529 three crops, thus we can simulate IWP for each main crop in every HRU. The RIWP of the three
530 main crops showed a trend of decline during the period of 2006-2010 (Fig. 9a-e). This was mainly
531 attributed to the increasing irrigation quota, as the excess water lowered the IWP. Whereas, during
532 the period of 2011-2013 (Fig. 9f-h), the RIWP of the three main crops showed an increasing trend.
533 This was because that the irrigation quota was reduced over this period, and the contribution of
534 groundwater compensated the crop yield losses. With less irrigation water applied, the number of
535 “red HRUs” will increase along with it.

536 Under a given irrigation water distribution, the spatial distribution of ET was the key factor
537 controlling the RIWP distribution. And the spatial distribution of ET was fundamentally determined
538 by the solar energy, and the water and salt dynamics of soil. Recall that the climate and, therefore,
539 the solar energy, was homogeneous in JFID. Then, the spatial heterogeneity of RIWP must be
540 attributed to the water and salt heterogeneity caused by the spatial heterogeneity of the cropping
541 pattern, groundwater table depth, and irrigation and drainage networks. Particularly, when the
542 farmlands had limited supply of irrigation water, the groundwater table depth and salinity played an
543 important role on IWP. Through the drainage ditches, groundwater could drain both water and salt
544 out of the field, thus the groundwater table level declines and the soluble salt content going upward
545 along with groundwater evapotranspiration to crop root zone decreases. Despite the negative effect
546 of draining water on IWP, the positive effect of draining salt out of the field will positively affect
547 IWP. As we can see in Fig. 9, the simulated IWP values for three crops were lower in the south, west,
548 north and north-west of the JFID than in the other regions. The south of the JFID is the main canal
549 for water diversion, which provide higher irrigation quota than other regions, in which results in a
550 lower IWP. For the west of JFID, it is mainly uncultivated area, thus the IWP is lower than other
551 regions. In the north-west of the JFID, main drainage ditch received the drainage water with high
552 saline content from four sub-main ditches and drained all the way to the north of JFID. Ditch seepage

553 water with high salinity resulted in the severe soil salinization in the north and north-west of JFID,
554 which will restrict the crop growth and lower the IWP. Thus, properly groundwater drainage
555 management and dealing with salt accumulation at the end of main drainage ditches in an irrigated
556 area is also a pressing and unsolved problem for increasing the “red HRUs”, which needs to be
557 figured out by irrigation managers.

558 As the major food-producing region of China, improving water productivity means producing
559 greater amounts of food crops with less amount of water, based on local or regional potential. With
560 declining access to water resources, farmers will need to grow different crops to maintain or increase
561 crop production profitability in the future. The comparison between the RIWP of different crops
562 (comparing the three columns in Fig. 9) showed that maize had the highest IWP, wheat had the
563 lowest IWP, and the IWP of sunflower was in the middle. Therefore, modestly increasing the
564 planting area of maize will improve the crop production per unit irrigation water amount. In addition,
565 the RIWP of sunflower is a little higher than that of wheat, and the benefit and the salt tolerance of
566 sunflower are both much higher than those of wheat. Thus, planting sunflowers should be promoted
567 in the JFID when available irrigation water resources is declining in the future, and this practice will
568 definitely increase the “red HRUs”.

569 **3.2.2 The impact of irrigation water depth applied and groundwater table depth** 570 **on irrigation water productivity**

571 In arid shallow groundwater area, irrigation water productivity (IWP) is affected by irrigation
572 water depth (IWD) applied and groundwater table depth (h_g). In all the four simulated h_g ranges,
573 IWP decreased when IWD increased (Fig. 10a), which was consistent with Huang et al. (2005).
574 Moreover, the magnitude of IWP decrease per unit increase of IWD was different under different
575 h_g ranges. The magnitude of IWP decrease under shallower h_g was smaller than that under deeper
576 h_g . This effect of increasing h_g on the relationship between IWP and IWD was consistent with Gao
577 et al. (2017). The above results indicate that when irrigation water is insufficient, groundwater can
578 compensate the crop water demand. However, when irrigation water is excessive, a large
579 proportion will eventually drain through the drainage ditches, and the IWP drops. Additionally,
580 among the four h_g ranges, the highest IWP was obtained in the range of 2-3m (Fig. 10b), which

581 was consistent with Xue et al. (2018). This indicates that a h_g deeper than that provides insufficient
582 water for crop growth; whereas, a h_g shallower than that will increase root zone soil salinity and
583 salt stress of crops. The negative effect of shallow groundwater salinity can also be found in Fig.
584 10a when h_g is less than 2m, and it indicates that when irrigation applied decreased from
585 300<IWD<400mm to 200<IWD<300mm it leads to decreases in IWP, which is caused by faster
586 reduction of ET than irrigation applied. Shallow buried groundwater contribution will make up for
587 ET reduction when smaller irrigation water applied, thus there exists another reason accelerate the
588 reduction of ET. We deduced that less irrigation water will weaken the role of irrigation on salt
589 leaching and result in more severe salinization in crop root zone. The negative effect of salt stress
590 on crop water use is greater than the positive effect of shallow groundwater contribution on crop
591 water use at this situation. Thus, keeping the groundwater table depth in the optimal range and
592 sustainable is of great importance to reach higher crop IWP at the regional scale, irrigation
593 managers may need to reasonably determine the irrigation quota and constantly maintain the
594 drainage system. Groundwater sustainability includes spacing withdrawals to avoid excessive
595 depletion and taking measures to safeguard or improve groundwater quality. To achieve this,
596 regional irrigation managers may need to take monitoring efforts to establish historic and current
597 conditions, research to model groundwater systems, forecast future variation, and policy to
598 manage activities influencing groundwater table and quality.

599 **4. Conclusions**

600 In view of the heterogeneous conditions of irrigated areas, taking fully consideration of the supply,
601 consumption and drainage processes of irrigation water and groundwater, a distributed RIWP
602 model was developed to couple the irrigation water flow processes along main canals and drainage
603 processes, water and salt transport processes in soil profile, groundwater water and salt lateral
604 transport, and agricultural water productivity module. Especially, a new method was designed and
605 incorporated to couple regional soil hydrology process and groundwater flow, with the spatial
606 difference of cropping pattern. Taking advantages of remote sensing and GIS tools, the
607 quantitative distributed RIWP model needs fewer soil and groundwater hydraulic parameters and
608 crop growing parameters and only readily available data of several observation sites at the

609 regional scale, and regional water and salt process can be simulated on a daily time step. Despite
610 the simplifications involved, the proposed methods of irrigation canal and drainage ditches
611 digitization and groundwater-runoff lateral exchange simulation between grids make the spatial
612 IWP simulation in a real distributed way, instead of using a field scale model applied in a
613 distributed mode to simulate all simulation units independently. The calibration and validation
614 results indicates a good performance of RIWP model applied in this typic study area, and spatial
615 distribution of IWP for different crops can be produced.

616 Programmed in Matlab (Mathworks Inc., 2015), RIWP model can be run on different operating
617 systems. Furthermore, the model includes capability for parallelization of simulations to reduce
618 batch run times when conducting simulations over large areas, conditions, and/or time periods. In
619 the nearly future, enabling the code to be linked quickly with other disciplinary models to support
620 integrated water resource management could be a great improvement of RIWP model. Also, we
621 are going to develop a website used for long-term distribution of the RIWP model and associated
622 documentation. Finally, RIWP model could improve knowledge of best practices to enhance water
623 productivity for key irrigation decision-makers. The simplicity of RIWP model in its required
624 minimum input data, which are readily available or can easily be collected, makes it user-friendly.
625 It is also a very useful model for scenario simulations and for planning purposes, which can be
626 used by economists, water administrators and managers working in the arid irrigated area with
627 shallow groundwater.

628

629 **Data availability**

630 The simulation results of the water budget during the simulation period of the JFID in this study
631 are available from the authors upon request (jiyxue@ucdavis.edu).

632

633 **Author contributions**

634 JYX and ZLH developed the idea to develop the conceptual RIWP model for irrigated area in arid
635 region with shallow groundwater and complex cropping patterns. JYX wrote the programming
636 code of the RIWP model in Matlab. JYX collected and processed the multiple datasets with the

637 help of SW, GHH and XX and prepared the paper. The results were extensively commented on
638 and discussed by ZLH, IW, IK, ZPS, and CZW.

639

640 **Competing interests**

641 The authors declare that they have no conflict of interest.

642

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649

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781• **Table Captions**

782 Table 1. The significance level of the input parameter to the model output variables

783 Table 2. Calibrated crop parameters of wheat, sunflower and maize for regional irrigation water
784 productivity model

785 Table 3. The collected possible parameter variation ranges and calibrated values of the parameters
786 describing soil hydraulic characteristics (K_e , S_y , K) and irrigation and drainage system (η_{lc} , η_{fc} , γ_d ,
787 A , m).

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810 Table 1. The significance level of the input parameter to the model output variables

<i>SRC</i> value	Significance level
$0.8 \leq SRC \leq 1$	Very important
$0.5 \leq SRC \leq 0.8$	Important
$0.3 \leq SRC \leq 0.5$	Unimportant
$0 \leq SRC \leq 0.3$	Irrelevant

811

812 Table 2. Calibrated crop parameters of wheat, sunflower and maize for regional irrigation water

813 productivity model

Parameters	Calibrated value		
	Wheat	Sunflower	Maize
Rate of yield decrease per unit of excess salts, <i>b</i> (%/ds/m)	7.1	12	12
Average fraction of TAW that can be depleted from the root zone before moisture stress, <i>p</i> (-)	0.55	0.45	0.55
Crop coefficient at crop initial stage, <i>k_{c1}</i> (-)	0.3	0.3	0.3
Crop coefficient at crop development stage, <i>k_{c2}</i> (-)	0.73	0.8	0.75
Crop coefficient at mid-season stage, <i>k_{c3}</i> (-)	1.15	1	1.2
Crop coefficient at last season stage, <i>k_{c4}</i> (-)	0.4	0.7	0.6
Yield response factor, <i>K_y</i> (-)	1.15	0.95	1.25
Electrical conductivity of the saturation extract at the threshold of <i>EC_e</i> when crop yield firstly reduces below <i>Y_m</i> at last season stage, <i>EC_{et}</i> (dS/m)	5	1.7	2

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828 Table 3. The collected possible parameter variation ranges and calibrated values of the
 829 parameters describing soil hydraulic characteristics (K_e , S_y , K) and irrigation and drainage system
 830 (η_{lc} , η_{fc} , γ_d , A , m).

Parameters	Description	Value range		Calibrated value
		Min	Max	
K_e	Soil evaporation coefficient, (-)	0.1	0.35	0.25
η_{lc}	Water utilization coefficient of lateral canal, (-)	0.81	0.91	0.88
η_{fc}	Water utilization coefficient of field canal, (-)	0.81	0.86	0.89
S_y	Specific yield, (-)	0.02	0.15	0.15
γ_d	Drainage coefficient, (-)	0.02	0.06	0.03
K	Permeability coefficient of unconfined aquifers, (mm/day)	731	12701	1150
A	Soil water permeability coefficient, (-)	0.7	3.4	3.4
m	Soil water permeability exponent, (-)	0.3	0.5	0.5

831 Note: The parameter value ranges were collected from local measurements, survey data and relevant research
 832 results. Soil texture of canal bed was silty sandy loam for 0-1 and 2-3 m depth below the ground, and sandy loam
 833 for 1-2 m. For silty sandy loam soil, the bulk density and saturated soil water conductivity are 502.3 mm d⁻¹ and
 834 1.42gcm⁻³, respectively. For sandy loam soil, the bulk density and saturated soil water conductivity are 1.49g cm⁻³
 835 and 592.6 mm d⁻¹, respectively. There were fine sand and sandy soil in the phreatic layer.

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850 **Figure Captions**

851 **Fig.1.** Schematic diagram of the conceptual RIWP model and the coupling between its sub-
852 modules.

853 **Fig.2.** Schematic diagram of groundwater lateral runoff exchange between HRUs.

854 **Fig.3.** Schematic diagram of coupling soil water and salt dynamics, and groundwater level and
855 salinity. And the IWP evaluation in each HRU.

856 **Fig.4.** Procedure chart of regional irrigation water productivity simulation.

857 **Fig.5.** Location of the Jiefangzha Irrigation District.

858 **Fig.6.** Relationship between the simulated and measured values during the crop growing season in
859 calibration and validation period.

860 **Fig.7.** The comparison of the simulated and measured groundwater table depth for 4 typical sites
861 during the crop growing season in the years of 2006-2013. (Note: a- uncultivated area during the
862 years of 2006-2013; b- uncultivated area from 2006-2008, and sunflower field and maize field
863 from 2009-2013; c, d- sunflower, wheat and maize field in the years of 2006-2013)

864 **Fig.8.** Parameter sensitivity analysis results of model for the three output variables: (a) irrigation
865 water productivity, (b) groundwater table depth and (c) groundwater salinity.

866 **Fig.9.** Spatial distribution of irrigation water productivity for the three main crops during the
867 period of 2006-2013. Each line shows the RIWP for each year by ascending order. The left, middle
868 and right column shows the RIWP of wheat, sunflower and maize, respectively.

869 **Fig.10.** (a) Simulated regional irrigation water productivity under various groundwater table depth
870 (h_g) conditions with different irrigation water amount (I_n) applied, and (b) its statistical analysis
871 results. In Fig.10a, W, S and M represents wheat, sunflower and maize, respectively

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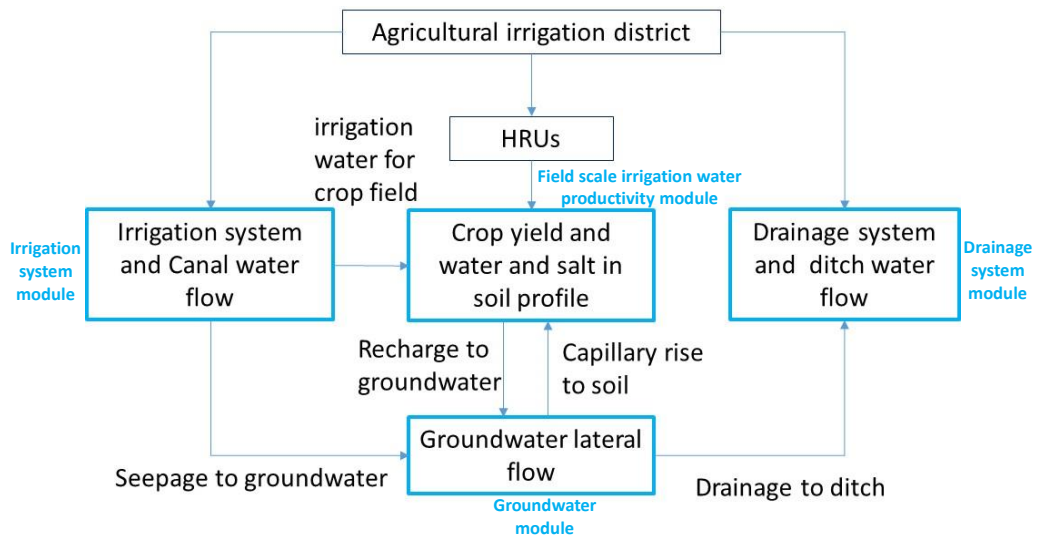
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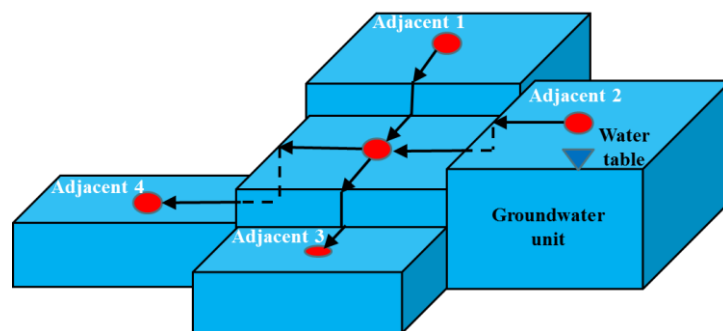
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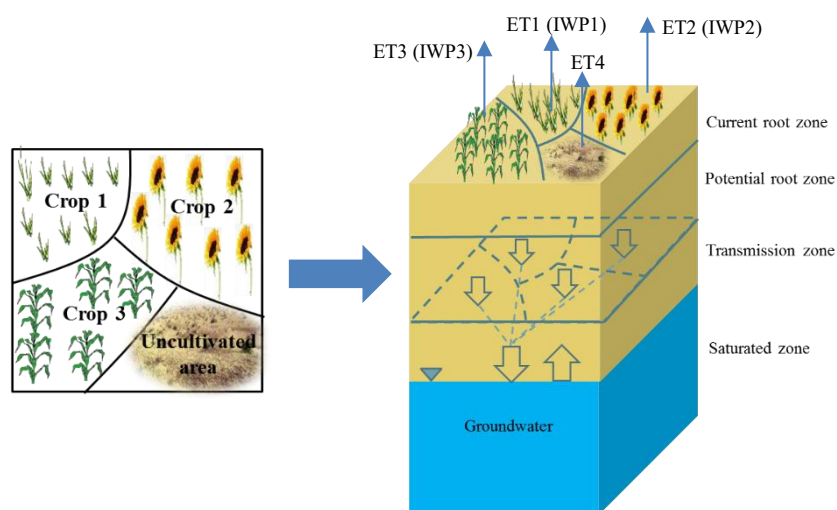
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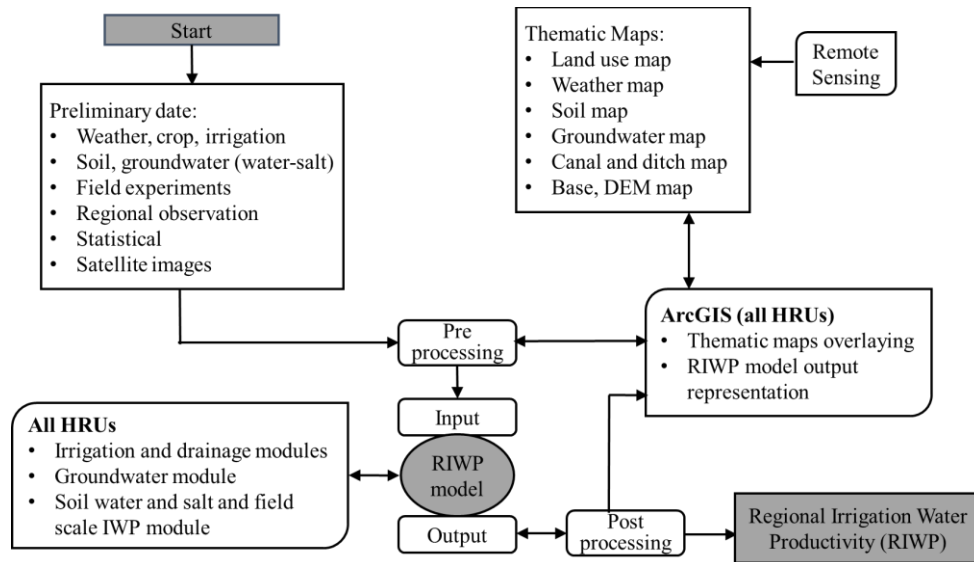
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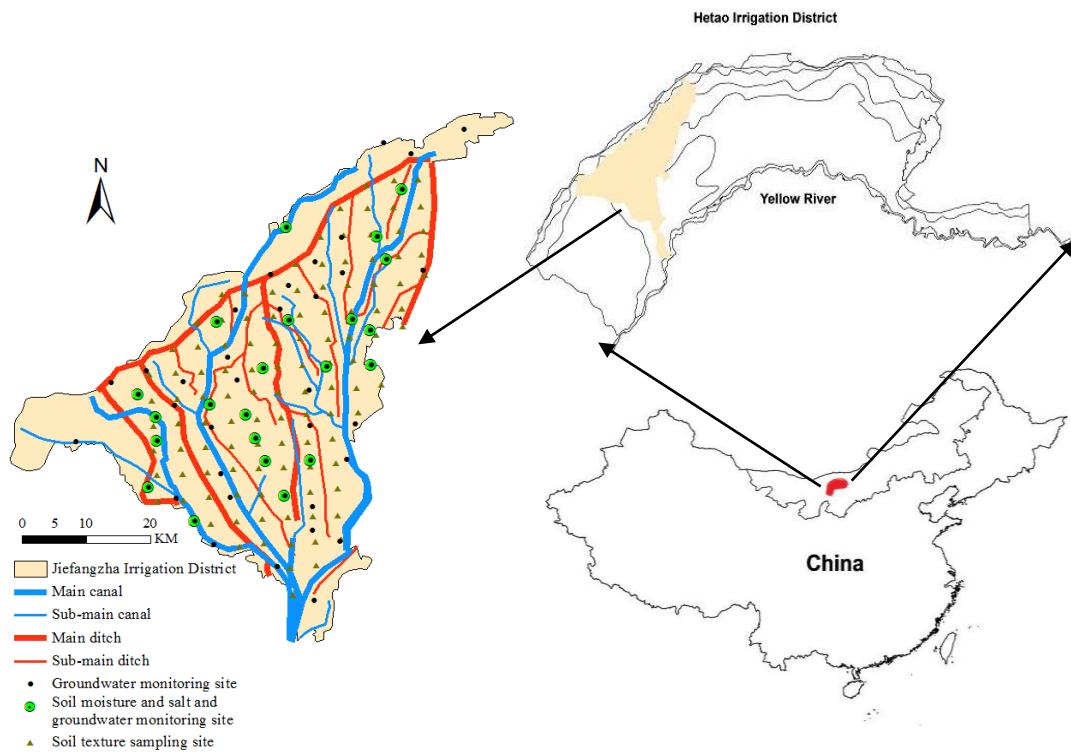


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888 **Fig.4.** Procedure chart of regional irrigation water productivity simulation.

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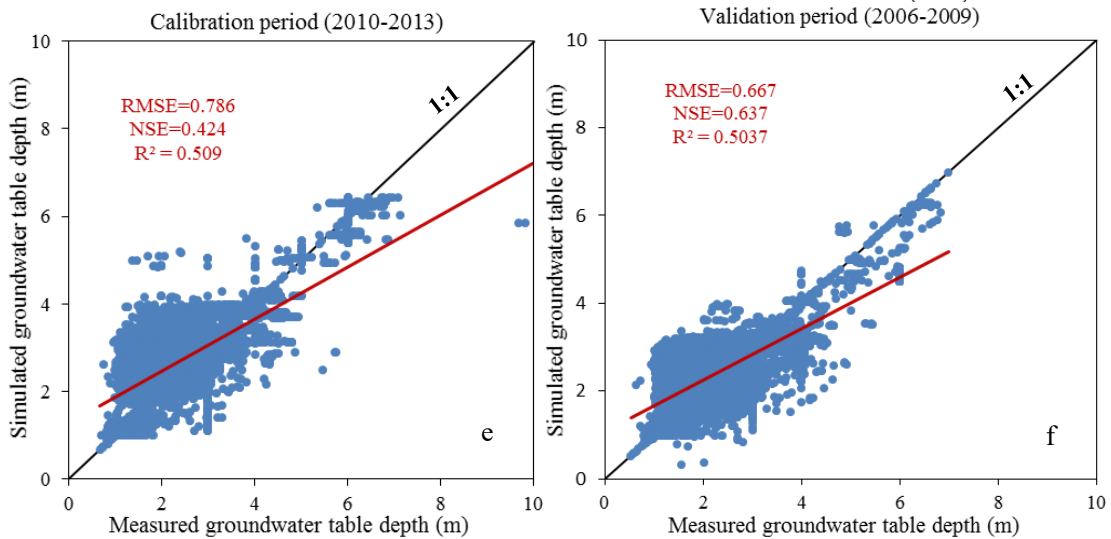
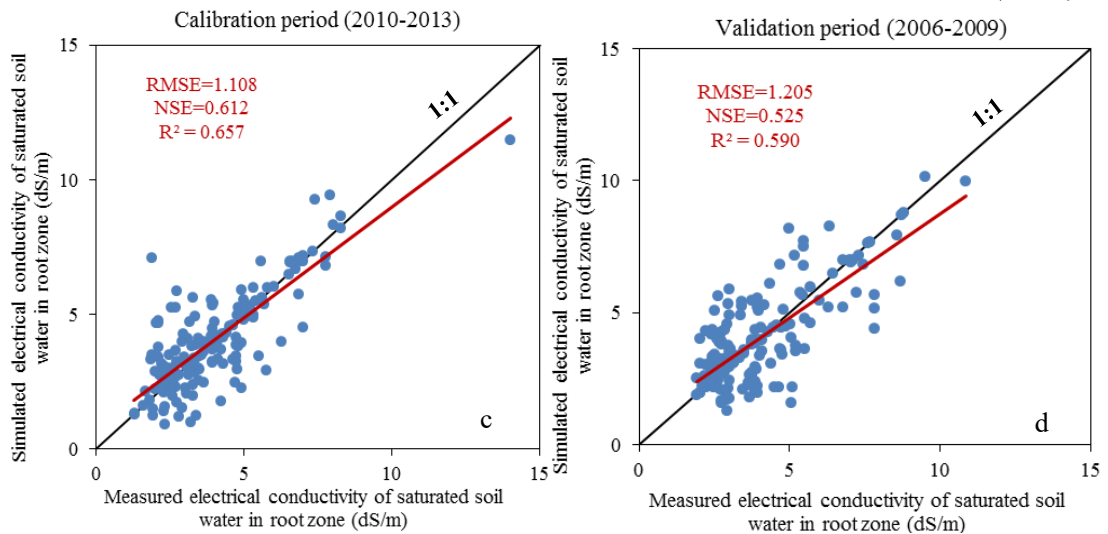
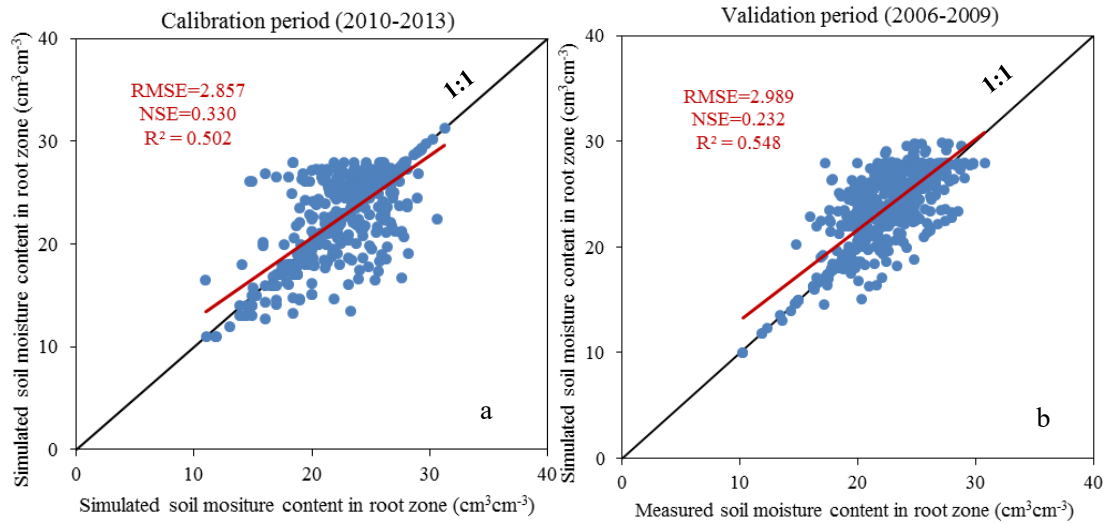
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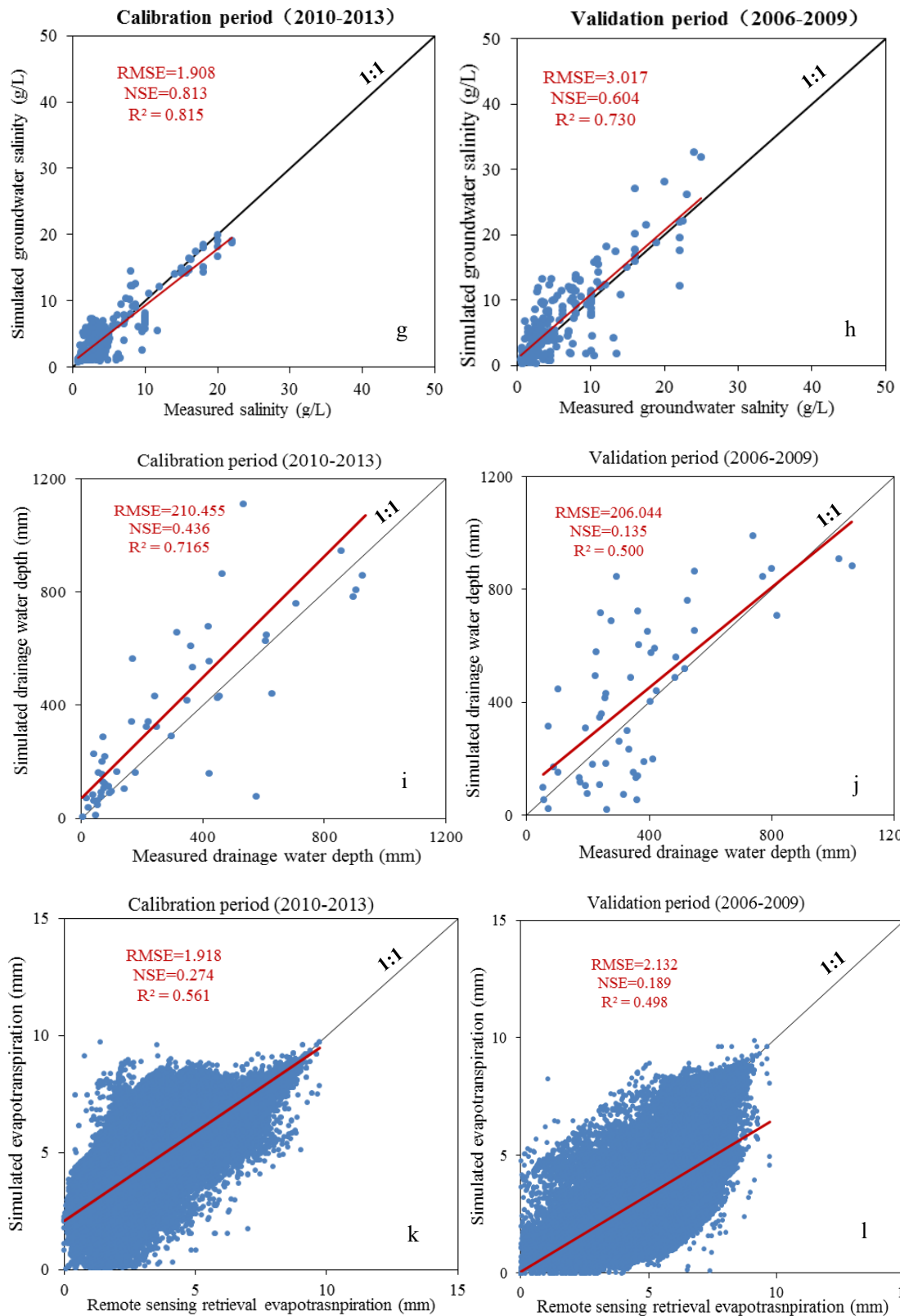
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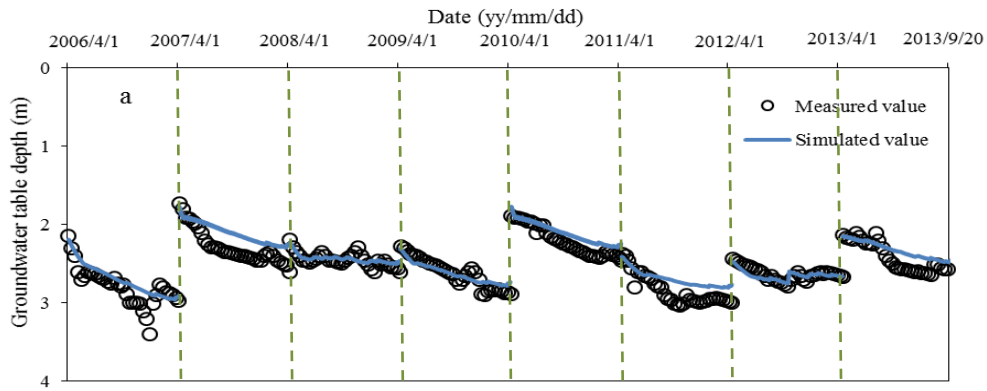


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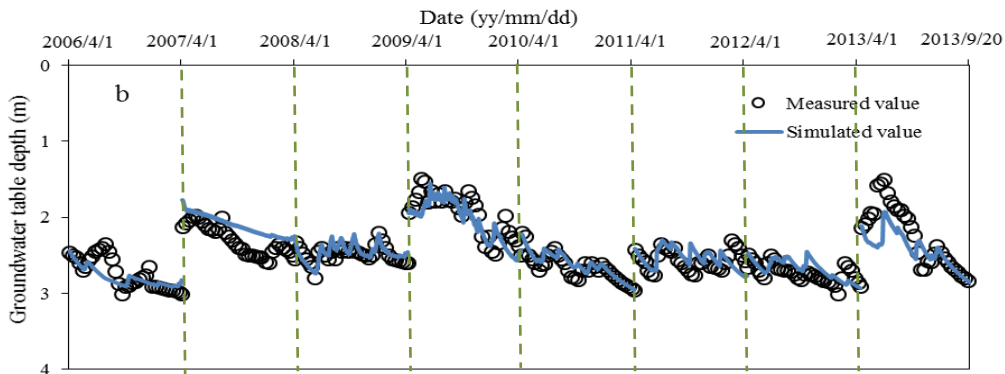
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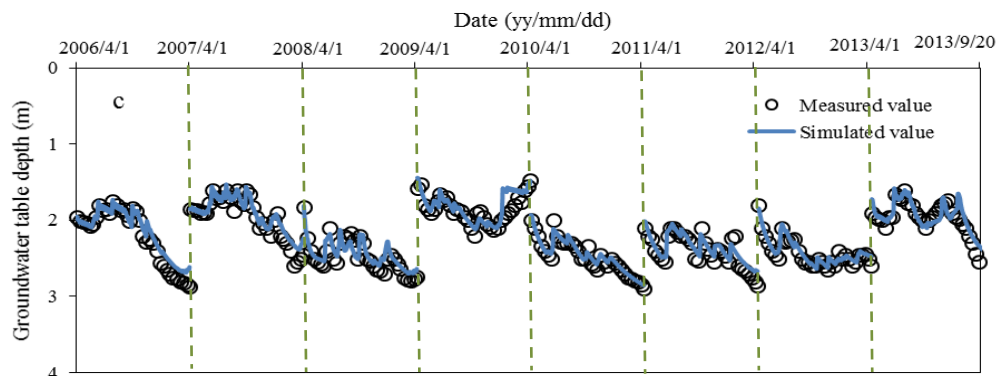
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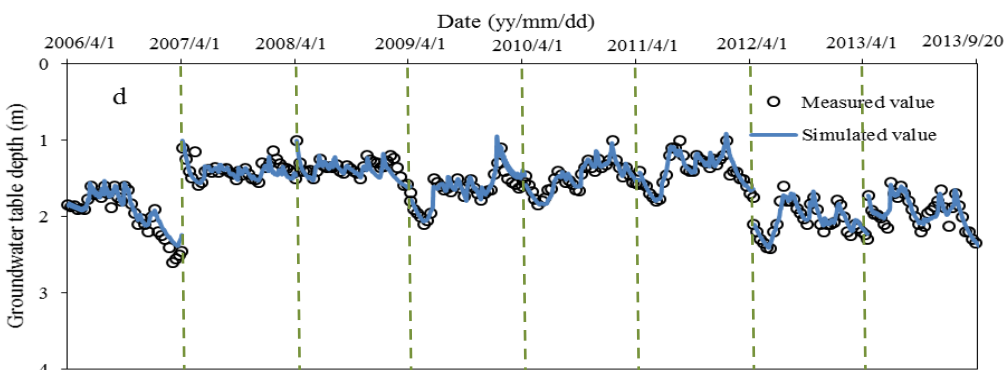
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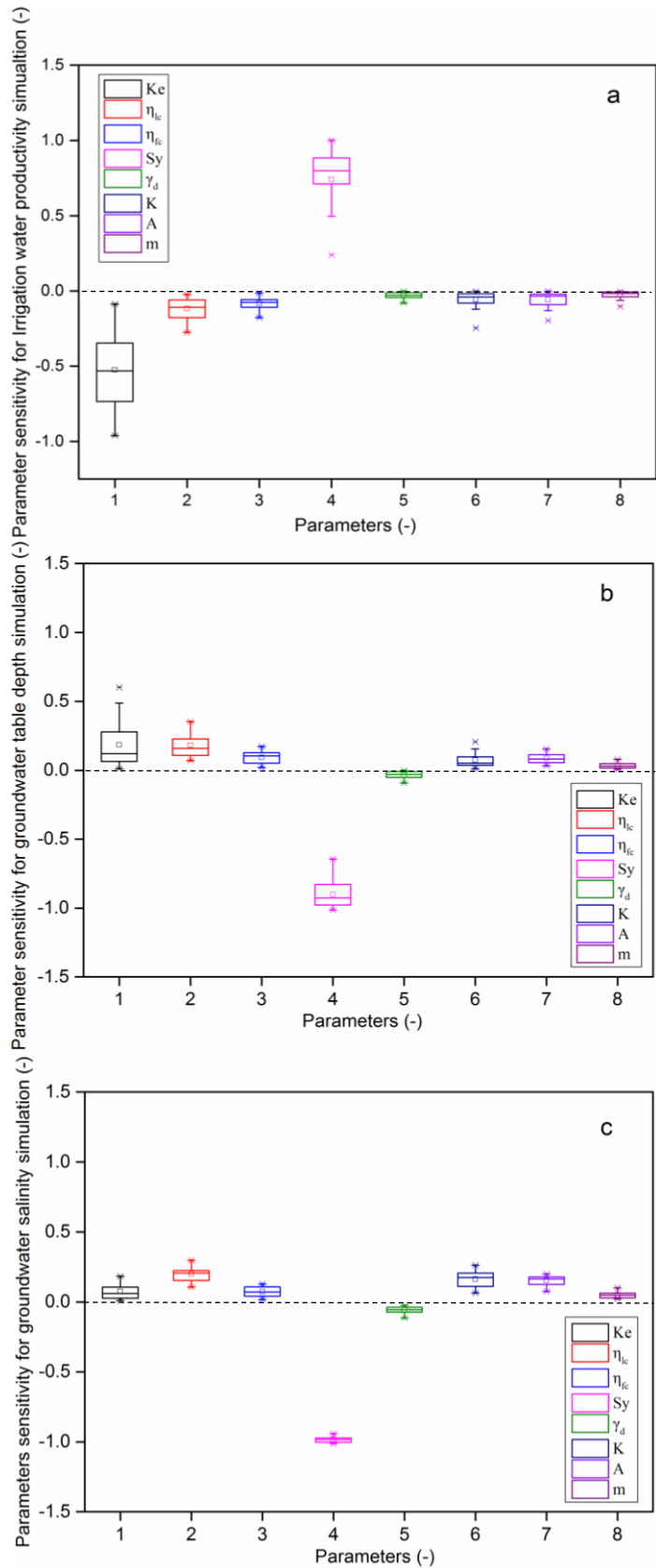


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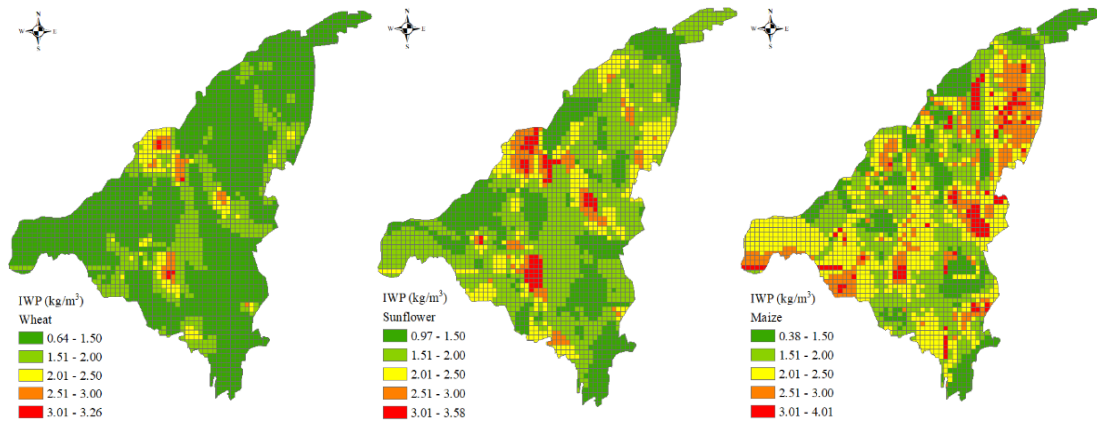
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916 **Fig.8.** Parameter sensitivity analysis results of model for the three output variables: (a) irrigation

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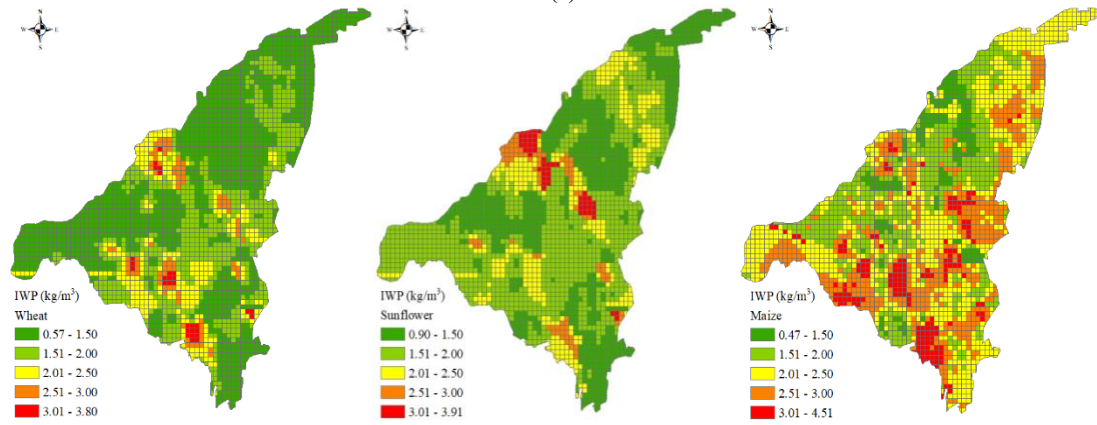
water productivity, (b) groundwater table depth and (c) groundwater salinity.



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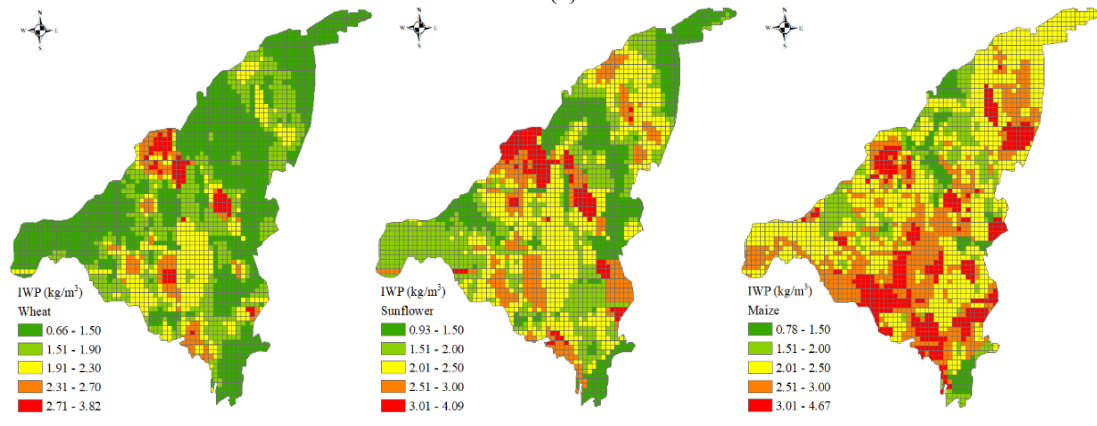
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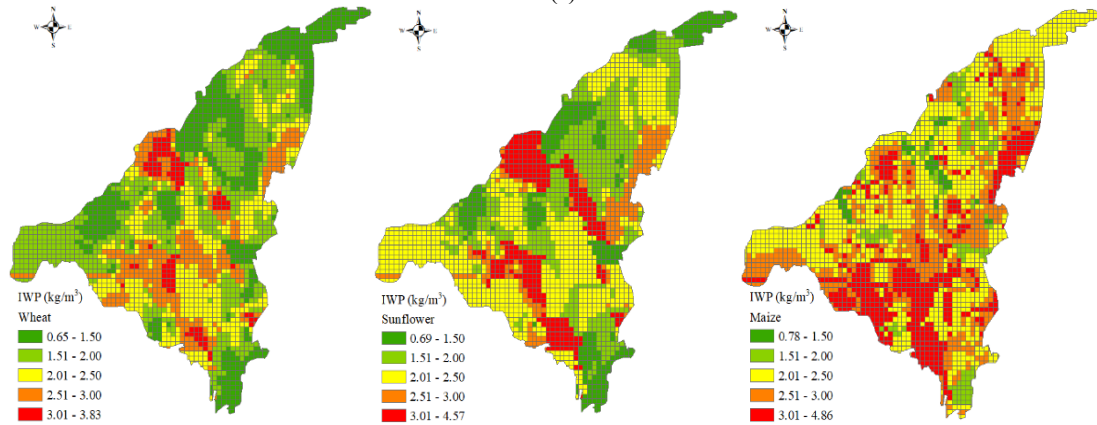
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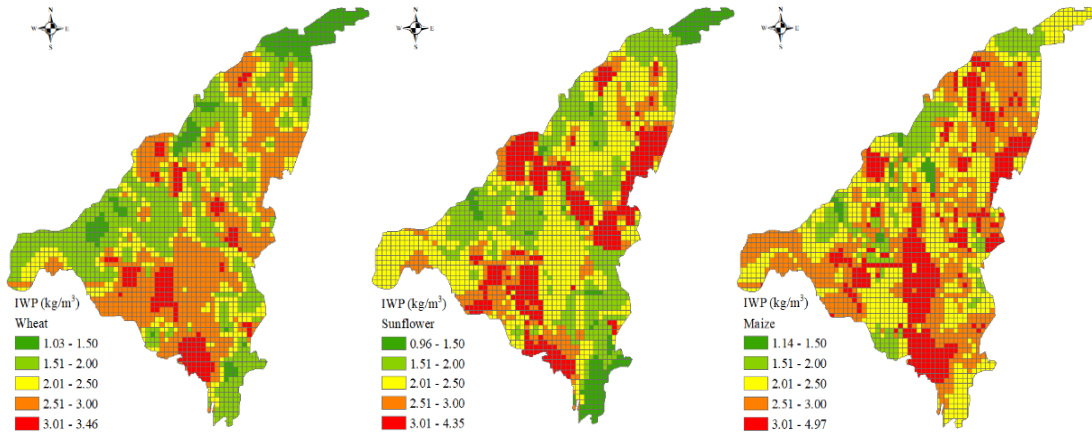
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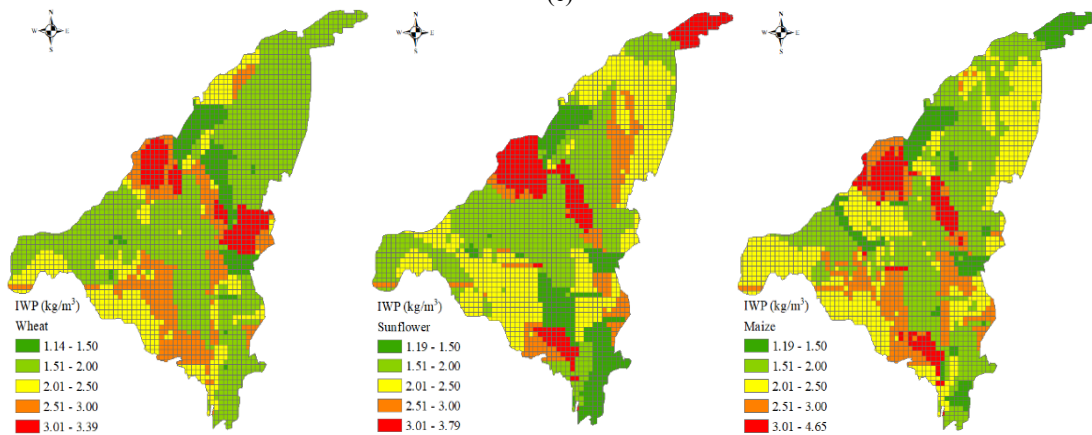
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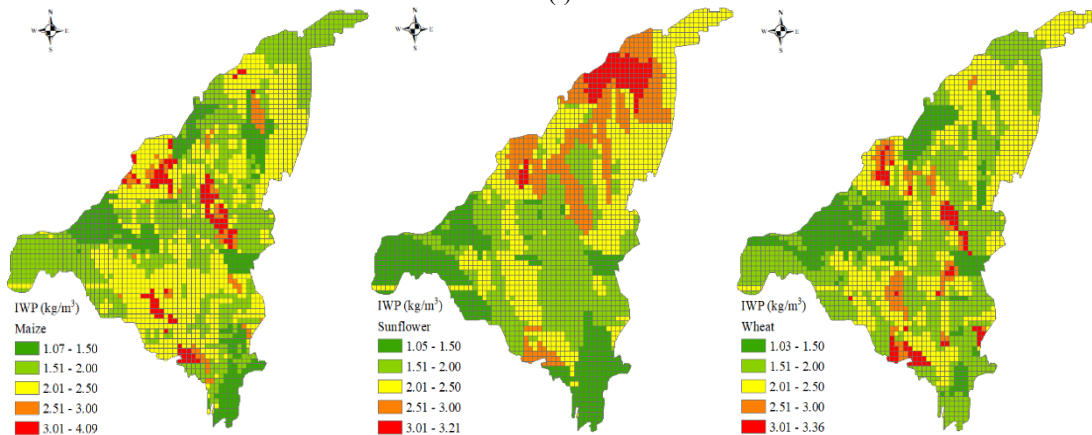
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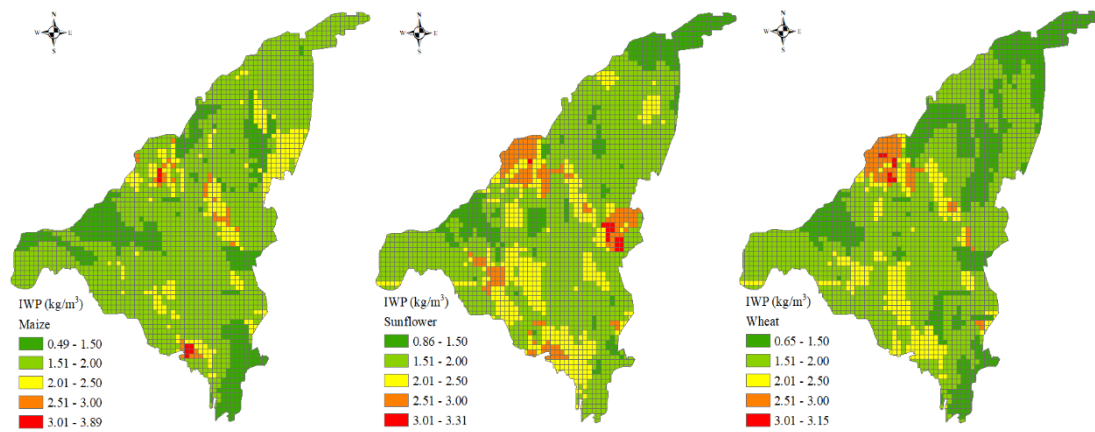
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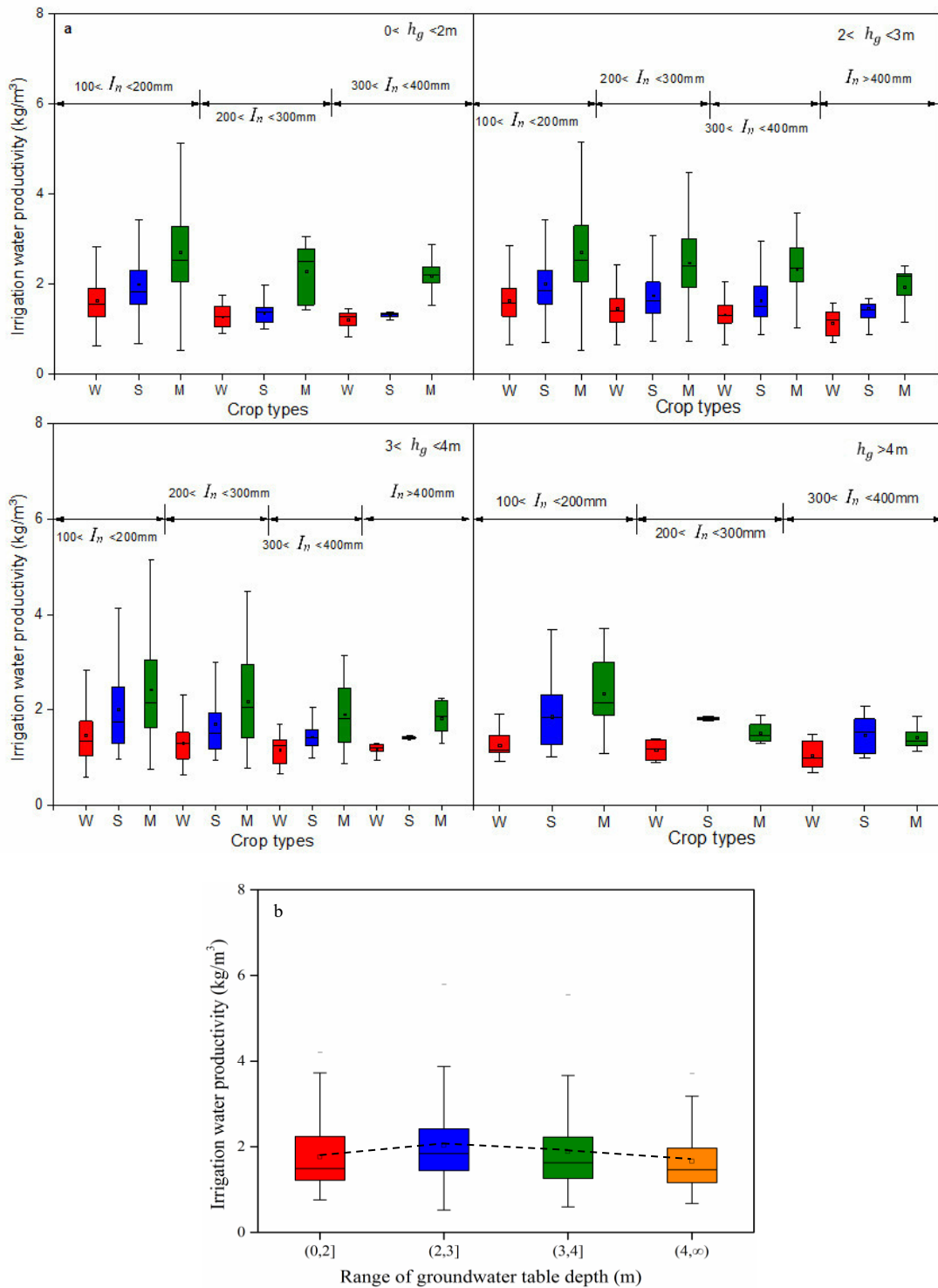
(g)



(h)

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