



1 **Toward high-spatial resolution hydrological modeling**
2 **for China: Calibrating the VIC model**

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17



18 **Abstract**

19 High-resolution hydrological modeling is important for understanding fundamental
20 terrestrial processes associated with the effects of climate variability and human
21 activities on water resources availability. However, the spatial resolution of current
22 hydrological modeling studies is mostly constrained to a relative coarse resolution
23 (~10–100 km) and they are therefore unable to address many of the water-related issues
24 facing society. In this study, a high resolution (0.0625°, ~6 km) hydrological modeling
25 for China was developed based on the Variable Infiltration Capacity (VIC) model,
26 spanning the period from January of 1970 to June of 2016. Distinct from other modeling
27 studies, the parameters in the VIC model were updated using newly developed soil and
28 vegetation datasets, and an effective parameter estimation scheme was used to transfer
29 parameters from gauged to ungauged basins. Simulated runoff, evapotranspiration (ET),
30 and soil moisture (SM) were extensively evaluated using in-situ observations, which
31 indicated that there was a great improvement due to the updated model parameters. The
32 spatial and temporal distributions of simulated ET and SM were also consistent with
33 remote sensing retrievals. Moreover, this high-resolution modeling is capable of
34 capturing flood and drought events with respect to their timing, duration, and spatial
35 extent. This study shows that the hydrological datasets produced from this high-
36 resolution modeling are useful for understanding long-term climate change and water
37 resource security. It also has great potential for coupling with the China Land Data
38 Simulation System to achieve real-time hydrological forecasts across China.

39



40 **1 Introduction**

41 Climate change and human activities impart substantial influences on hydrological
42 cycles and water resources, resulting in many challenges in multi-scale hydrological
43 research (Devia et al., 2015). Water-related research has largely been reshaped by the
44 need to solve practical problems, such as predicting floods and droughts, managing
45 water resources, and designing water supply infrastructures at finer scales (Kirchner,
46 2006). As an alternative solution, high-resolution hydrological modeling is key to
47 supporting analyses of land–atmosphere interactions, surface and subsurface
48 interactions, water quality, and human impacts on the terrestrial water cycle (Wood et
49 al., 2011) , and can serve as a benchmark for evaluating extreme events and for
50 preventing record-setting disasters in advance (Lee et al., 2017). Developing a high-
51 resolution hydrological modeling is also recognized as important for understanding the
52 implications of climate change (Zhu and Lettenmaier, 2007) and improving the ability
53 of scientists to narrow uncertainties and errors in water resources management (Scherer
54 et al., 2015).

55 At present, hydrological modeling are usually implemented at resolutions from 0.125°
56 to 2° latitude by longitude and with temporal resolutions from hourly to daily
57 (Cherkauer et al., 2003; Troy et al., 2008) across different regions, such as Mexico (Zhu
58 and Lettenmaier, 2007), Texas (Lee et al., 2017), and the Mississippi watershed
59 (Scherer et al., 2015). China is one of the most interesting study areas for many
60 researchers and hydrological modeling of China have also been simulated in a variety
61 of studies (Wang et al., 2011; Wang et al., 2012; Xie et al., 2007; Zhang et al., 2014).



62 However, many terrestrial hydrologic and vegetative states and fluxes are typically
63 constrained at rather coarse spatial resolutions (~10–100 km), which cannot adequately
64 address critical scientific questions about the water cycle (Wood et al., 2011) or to
65 describe hydrological process and water dynamics in small watershed, especially when
66 there is a need to detect the impact of extreme events.

67 In recent decades, many devastating natural disasters have occurred frequently
68 worldwide and in China due to global climate change (Mo et al., 2016; Piao et al., 2010;
69 Xu et al., 2015). The intensification of droughts and floods is having a critical negative
70 impact (i.e., economic losses, agricultural destruction) in China (Zhang et al., 2015).
71 Therefore, high-resolution hydrological modeling in China is urgently needed to
72 identify and monitor the underlying processes and intensities of hydrological extremes
73 (Dong et al., 2011) and to reflect the regional details of climate change patterns (Zhang
74 et al., 2006).

75 However, there are disadvantages and difficulties in developing high-resolution
76 hydrological modeling in China with respect to meteorological forcings, soil and
77 vegetation datasets, and model evaluation. First, meteorological forcing data hold
78 substantial uncertainties, especially for high-resolution modeling, because ground-
79 based observation stations are limited in China. Only ~750 meteorological stations for
80 collecting data (which may be combined with remote sensing datasets) have been
81 commonly used to generate different resolutions of forcing data (Xu et al., 2015; Zhai
82 et al., 2005; Zhang et al., 2014), and these datasets are only suitable for modeling at
83 coarse resolutions (> 10 km) rather than at high-resolutions. Second, estimating model



84 parameters presents a great challenge because the climate, soil, and land cover
85 conditions are highly heterogeneous over the 9.6 million km² area of China (Zhai et al.,
86 2005). Third, ground-based hydrological stations are extremely scarce in most basins,
87 and hydrological datasets are insufficient for model calibration and validation. Thus, in
88 many studies, model parameters have only be calibrated using limited streamflow data,
89 while evapotranspiration (ET) and soil moisture (SM) states have not been well
90 evaluated (Jiao et al., 2017; Scherer et al., 2015). Finally, remote sensing (RS) data can
91 serve as hydrological model inputs; however, RS data have not been fully combined
92 with hydrological modeling, although they have the potential to improve model
93 performance (Wu et al., 2014).

94 In this study, we attempt to develop a high-resolution hydrological modeling framework
95 for China at the spatial resolution of 0.0625° (~6 km). The framework is based on a land
96 surface hydrological model, (i.e., the Variable Infiltration Capacity (VIC)) (Liang, 1994,
97 1996). The features of this framework include: (1) it is driven by meteorological forcing
98 data that were generated based on data from relatively high-density ground-based
99 stations (2481 stations), nearly tripling the number of meteorological stations when
100 compared with other studies (Pan et al., 2012; Xie et al., 2007; Zhang et al., 2014); (2)
101 soil parameters of the VIC were updated based on a newly developed soil dataset for
102 China, which provides an improved representation of hydrological and biogeochemical
103 characteristics (Dai et al., 2013; Shanguan et al., 2013); (3) an effective scheme was
104 employed to estimate model parameters for ungauged basins; (4) the simulated runoff,
105 ET, and SM were extensively evaluated using ground-based measurements and RS data



106 products.

107 This high-resolution modeling framework has attractive applications and potential
108 extensions. The simulated hydrological flux and state variables are useful for
109 understanding long-term climatic changes and water resource security at various scales.
110 Additionally, these simulated variables, benefiting from the high resolution of the
111 modeling, can provide more detailed information for detecting drought and flood events
112 at the regional scale. Furthermore, the framework can be extended to couple with the
113 China Land Data Simulation System (CLDAS), which provides real-time
114 meteorological inputs and SM conditions at the same resolution (0.0625°) (Shi et al.,
115 2011). This hydrological modeling, driven by high-quality and real-time inputs from
116 CLDAS, may improve the accuracy of results and estimate real-time hydrological
117 processes.

118 In the next section we describe the structure of the VIC model, including its inputs data
119 and parameters. The method of calibration and transfer parameters is also presented. In
120 section 3, we describe the evaluation of model performance over China and the
121 application of the modeling on extreme events. We discuss its reliability, and potential
122 and limitation in section 4, and in section 5 we present our conclusions and thoughts on
123 future directions.

124 **2. Data and methods**

125 **2.1 Hydrological model**

126 The VIC model is a distributed and physically based model that solves for the surface
127 energy and water balance (Liang, 1994, 1996). Variable Infiltration Capacity model



128 simulates SM, ET, snow pack, surface runoff, baseflow, and other hydrological
129 variables in daily or sub-daily time steps. Each grid cell is partitioned into multiple
130 vegetation types, and the soil column has three soil layers, where each layer
131 characterizes the dynamic response of the soil to climatic conditions. The VIC model
132 characterizes multiple land cover types, with one type of bare soil. Each vegetation type
133 has a leaf area index (LAI), minimum stomatal resistance, roughness length,
134 displacement length, and relative fraction of the root (Umair et al., 2018).

135 This model is selected for use in this study due to three main advantages: (1) a simple
136 conceptual rainfall–runoff model is used that allows the spatial representation of
137 gridded topography, infiltration rate, soil properties, climate variables, and land covers,
138 which are important factors in modeling runoff under spatially heterogeneous
139 conditions (Tesemma et al., 2015); (2) both infiltration and saturation excess runoff
140 generation mechanisms are considered in the model, making it suitable for application
141 to both arid and humid regions; (3) simulations of snow and frozen soil processes,
142 which are necessary for the Tibet Plateau, can be performed. Finally, the VIC model
143 has also been shown to represent land surface hydrologic processes well in numerous
144 studies (Luo et al., 2013; Wu et al., 2014), and has been used from global (Bart Nijssen
145 et al., 2001; Haddeland et al., 2007) to river basin scales (Liang and Xie, 2001) to assess
146 water resources, land–atmosphere interactions, and overall hydrological budgets.

147 **2.2 Data for model inputs**

148 **2.2.1 Meteorological forcing data**

149 The VIC model is driven by historical meteorological forcing, including precipitation



150 (mm), minimum and maximum temperature ($^{\circ}\text{C}$), and wind speed (m/s). We ran the
151 model in daily time steps from 1970–2016 in a water-balance mode. All of the forcing
152 data were produced by interpolating ground-based observations from 2481
153 meteorological stations in China (Fig. 1a), which were obtained from the China
154 Meteorological Administration (CMA). These data were interpolated into a gridded
155 dataset (at a resolution of $0.0625^{\circ} \times 0.0625^{\circ}$) by a linear interpolation method using
156 an inverse squared distance between the stations. At least five stations around the target
157 grid were searched to conduct this interpolation. A lapse rate of $-6.5^{\circ}\text{C km}^{-1}$ with
158 respect to the elevation difference between the station and the target grid was used to
159 reflect the decrease in temperature with increasing elevation. The same interpolation
160 method for generating gridded forcing data has been successfully applied in previous
161 VIC simulations(Xie and Cui, 2011; Xie et al., 2015; Xie et al., 2007).

162 **2.2.2 Vegetation dataset**

163 Vegetation data needed for VIC simulations included land cover (LC) types and
164 associated vegetation parameters. Details of the LC types were originally created by
165 merging a number of Land Satellite Thematic Mapper (Landsat TM) images (Liu et al.,
166 2010), with a spatial resolution of 1 km. There were 12 types of LC distributed across
167 China. Based on these LC types, the fractional area of each vegetation type in a grid
168 cell was calculated.

169 The parameters for each type of vegetation (e.g., the architectural resistance) are
170 available from ftp://ftp.hydro.washington.edu/pub/HYDRO/models/VIC/Veg/veg_lib,
171 except for the LAI. The LAI reflects the amount of available leaf material, and thus,



172 represents the canopy density and growth of vegetation, and influences the ET process
173 (Hanes and Schwartz, 2010). Monthly LAI data at a spatial resolution of 0.1° (~ 8 km)
174 were obtained from the Advanced Very High Resolution Radiometer (AVHRR)
175 satellites acquired between January of 1982 and December of 2006, and they were
176 derived from an 8-km composited AVHRR Normalized Difference Vegetation Index
177 (NDVI) (Strahler et al., 1999). Hence, based on the LC maps and the LAI data,
178 vegetation parameters were generated for use in the VIC simulations.

179 **2.2.3 Soil dataset**

180 Soil datasets define the soil physical and chemical properties of grid cells. In this study,
181 detailed information on the physical and chemical properties of soils were obtained
182 based on a 30×30 arc-second-resolution soil characteristics dataset (Dai et al., 2013;
183 Shangguan et al., 2013) derived by using the 1:1,000,000 Soil Map of China and 8595
184 representative soil profiles.

185 This dataset is specifically suitable for land surface modeling, so it can be incorporated
186 into hydrological models to better represent the role of soils in hydrological and
187 biogeochemical cycles in China. Four influential soil parameters (i.e., field capacity,
188 wilting point, saturated hydraulic conductivity, and bulk density) for each of the three
189 layers were obtained from the soil dataset (Dai et al., 2013; Shangguan et al., 2013) and
190 then applied to the 0.0625° grid in this study. The other soil parameters, such as the
191 thermal damping depth, bubbling pressure, surface roughness of bare soil, and
192 snowpack were prescribed according to the Food and Agriculture Organization (FAO)
193 of the United Nations (UN) dataset, which has been successfully used by Nijssen et al.



194 (2000); Nijssen et al. (1999).

195 **2.3 Data for model evaluation**

196 **2.3.1 Streamflow**

197 The VIC model was first calibrated and validated using streamflow data. We obtained
198 streamflow data for 29 stations from the Annual Hydrological Report for P.R. China
199 (Fig. 1b). These stations are situated at the outlets of 29 sub-catchments that have
200 different climatic and LC conditions. The data were partitioned into two groups, 20
201 stations of data were used for calibration and the remaining 9 were then used for model
202 validation.

203 **2.3.2 Evapotranspiration (ET)**

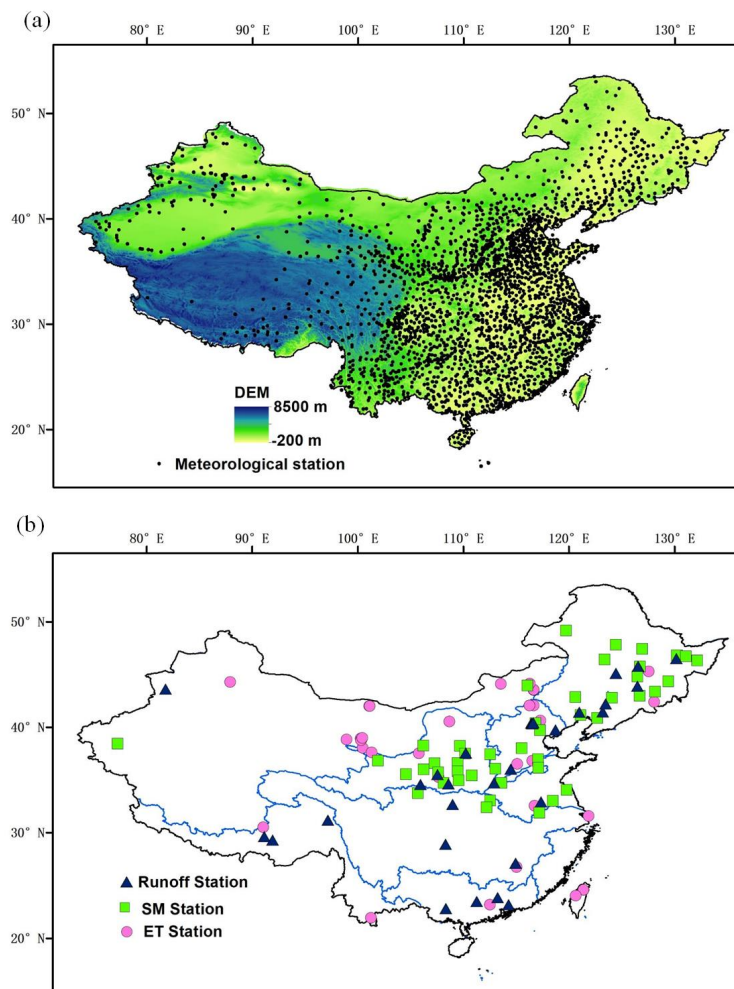
204 Evapotranspiration is the second largest term in the global land surface water budget
205 (Bohn and Vivoni, 2016), and it was evaluated in our model by using ground-based
206 observations and an RS product. Ground-based observations of ET were obtained at 33
207 covariance tower stations (Fig. 1b). The RS ET product was from the Global Land
208 Surface Satellite (GLASS) and, which merges multiple sources of RS data to achieve
209 reliable ET estimates (Liang et al., 2013; Yao et al., 2015; Yao et al., 2014; Zhao et al.,
210 2013), and thus it was used to spatially evaluate the VIC-simulated ET. Moreover, the
211 GLASS ET was approximately equal in spatial resolution (0.05°) to the model in this
212 study, and was therefore applicable to the evaluation of ET.

213 **2.3.3 Soil moisture (SM)**

214 Soil moisture plays an important role in the terrestrial hydrological cycle, and it also
215 connects agricultural drought events. Therefore, the validation of SM was also



216 performed in this study. Soil moisture data from 45 in situ stations across China (Fig.
217 1b) obtained from the CMA were for this assessment. To guarantee the reliability of the
218 validation results, we selected stations that were close to the center of a target grid and
219 covered a long measurement period. Except for the ground-based observation data, the
220 RS SM data are available from the European Space Agency Water Cycle Multimission
221 Observation Strategy and Climate Change Initiative projects (ESA-CCI SM). The ESA-
222 CCI product provides relatively consistent and reliable information for SM worldwide
223 (Qiu et al., 2016) and has been successfully validated by many researchers (Dorigo et
224 al., 2015; Wang et al., 2016).



225

226 **Figure 1: Distribution of (a) meteorological stations and (b) in situ runoff**

227 **stations, SM and ET stations.**

228 **2.4 Parameter calibration and transfer scheme**

229 **2.4.1 Parameter calibration**

230 After all of the necessary input data for the model were collected and prepared, the VIC

231 model was calibrated for the selected 20 basins and validated for the 9 basins located

232 in different climate zones (Fig. 1). Most basins were minimally affected by human



233 activities, such as water extraction, irrigation, and water management. Seven of the
 234 most sensitive VIC model parameters were targeted for calibration in each basin
 235 separately, including the infiltration curve, b , the depths of the three soil layers
 236 (d_1, d_2, d_3), the maximum velocity of the baseflow, D_{smax} , the fraction of the
 237 maximum baseflow velocity, D_s , and the fraction of the baseflow of the maximum
 238 SM where non-linear baseflow occurs, W_s . The parameters D_{smax} , D_s , W_s , and d_3 are
 239 influential for runoff and for early season SM and ET since they govern water
 240 infiltration and baseflow generation (Bennett et al., 2018). The initial values of these
 241 sensitive parameters were obtained from Zhang et al. (2014) at a 0.25° resolution and
 242 then were directly downscaled to a 0.0625° resolution. The calibration involved setting
 243 an identical parameter set for each basin to find the best combination of the seven
 244 parameters. It was performed via a trial and error procedure to match the simulations
 245 with the hydrograph observations.

246 Three metrics were used to evaluate model performance: (1) the correlation coefficient
 247 (R), (2) the Nash-Sutcliffe efficiency (NSE), and (3) the relative error (bias; %) between
 248 observations and simulations.

$$249 \quad NSE = 1 - \frac{\sum(Q_{i,obs} - Q_{i,sim})^2}{\sum(Q_{i,obs} - \overline{Q_{obs}})^2} \quad (1)$$

$$250 \quad Bias(\%) = \frac{\overline{Q_{sim}} - \overline{Q_{obs}}}{\overline{Q_{obs}}} \times 100\% \quad (2)$$

251 In Eqs. 1 and 2, $Q_{i,obs}$ is the observed flow in the i month, $Q_{i,sim}$ is the respective
 252 i th simulated flow from the model, and $\overline{Q_{sim}}$ and $\overline{Q_{obs}}$ are the observed and
 253 simulated mean annual discharges for the calibration period, respectively.

254 For each grid cell in the calibrated basins, an adjustment factor (Adj_factor) can be



255 defined as:

$$256 \quad Adj_factor = \frac{PAR_{final}}{PAR_{initial}} \quad (3),$$

257 where PAR_{final} and $PAR_{initial}$ are the final and the initial estimates of the parameter,
258 respectively. Based on this adjustment factor, the estimates of parameters in the
259 calibrated basins were transferred to the uncalibrated basins.

260 **2.4.2 Parameter transfer**

261 The area of China was divided into nine large river basins (Fig. 2) according to
262 topographic and LC conditions. As the VIC model parameters are closely related to
263 physical and climatic characteristics of basin properties, such as LC and meteorological
264 factors, we overlaid the river basins with climate zones to define a climatic similarity,
265 as described by Xie et al. (2007). Based on the climatic similarity and the adjustment
266 factor described in Sect. 2.4.1, the estimated parameters in calibrated basins were
267 transferred to the uncalibrated basins. The 20 independent, calibrated basins were
268 located in different climate zones and designed to estimate the parameters in their
269 uncalibrated, climate-related areas. Seven climatic zones in China, as defined based on
270 the Köppen classification criteria (Kottek et al., 2006), are shown in Table 1 and Fig. 2.
271 The parameter transfer strategy has been successfully used by Xie et al. (2007), and it
272 is briefly described as follows:

273 (1) The adjustment factors in each calibrated basin were used to adjust parameters in
274 uncalibrated basins;

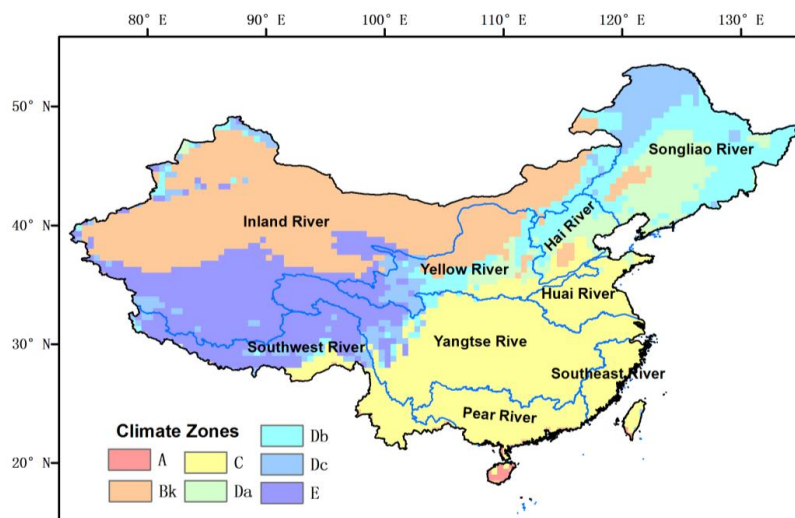
275 (2) The rainy climate zone was further divided into three parts according to basins of
276 the Huai River, Yangtze River, and Pearl River, as C1, C2, and C3, respectively;



277 (3) The tropical climate zone has similar climatic characteristics to the Pearl River basin.
278 Therefore, the parameters for the tropical climate zone were set to the same adjustment
279 values as C3;
280 (4) Parameters of southeastern basins were used as the equivalent multiple as the
281 Yangtze River basin C2;
282 (5) The Dc climate zones covers two different regions in northeastern and southeastern
283 China (Dc east and Dc west). Therefore, the parameters in Dc east and Dc west were
284 adjusted using the same multiples from the related Da and E zones, respectively.

285 **Table 1: Classification of Köppen climate zones.**

| Climate zones | Description | Criterion |
|---------------|--|---|
| A | Equatorial climate | $T_{min} \geq +18 \text{ }^{\circ}\text{C}$ |
| Bk | Dry, cold climate | $T_{ann} < +18 \text{ }^{\circ}\text{C}$ |
| C | Rainy, midlatitude climate | $-3 \text{ }^{\circ}\text{C} < T_{min} < +18 \text{ }^{\circ}\text{C}$ |
| Da | Continental climate with hot summer | $T_{max} \geq +22 \text{ }^{\circ}\text{C}$ |
| Db | Continental climate with cool summer | $T_{min} \leq -3 \text{ }^{\circ}\text{C}$ not (a) and at least 4 $T_{mon} \geq +10 \text{ }^{\circ}\text{C}$ |
| Dc | Continental climate with short cool summer | not (Bk) and $T_{min} > -38 \text{ }^{\circ}\text{C}$ |
| E | Polar climate | $T_{max} < +10 \text{ }^{\circ}\text{C}$ |



286

287

Figure 2: River basins and climate zones in China.

288 3. Results

289 3.1 Runoff calibration and validation

290 To highlight the advantages of updating soil model parameters, we conducted two
291 simulations: one using the original soil parameters, which were directly downscaled
292 from a 0.25° resolution, and the other employing the updated soil parameters with
293 parameter calibration. Figure 3 presents the monthly discharge of the simulations from
294 the original and calibrated parameters and observations over 9 river basins, which were
295 chosen to be regionally representative and distributed among diverse climates. The
296 model performance was considerably better when using the calibrated parameters rather
297 than the initial parameters (Sect. 2.4.1). For most basins, the simulations with defaults
298 parameters tended to have higher discharges, especially overestimating the peak flow
299 during summer, such as in Phujym, Jilin, Heishiguan, and Tsuang. In contrast, the
300 calibration was able to successfully avoid the overestimation of peak flow. However,



301 for the Shetang, Maojiahe, and Tsyamusy basins, which have little rainfall and runoff,
302 the initial parameters do not match the observations well at first during the low-flow
303 seasons, but this phenomenon changed after parameter calibration. Overall, the
304 comparisons revealed that the runoff dynamics were well captured after calibration, and
305 consequently the calibrated results were improved relative to the original VIC
306 simulations.

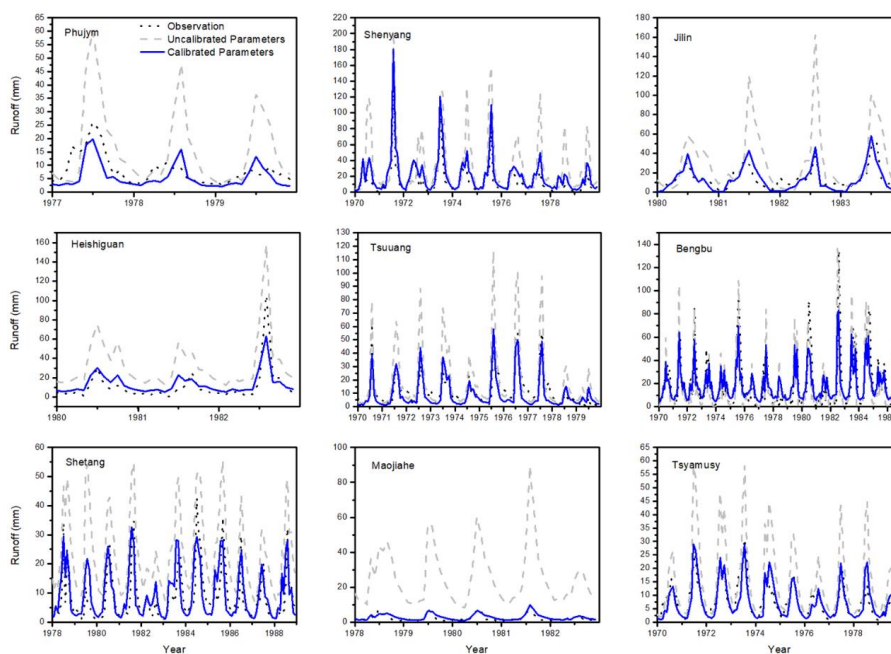
307 In Table 2, the model performances are listed for each basin after calibration and
308 validation. The correlation coefficient, NSE, and bias were used to evaluate the
309 simulations against observations. Most of the calibrated basins had high R and NSE
310 values of more than 0.70. The relative bias presented here is generally within 20%. The
311 simulations of basins located in southern China (e.g., C1, C2, and C3), which usually
312 receive abundant rainfall and experience substantial runoff throughout the entire year,
313 tended to have better agreements with observations than those in northern China (e.g.,
314 Da, Db, and Bk). In general, the calibration improved the results in all instances,
315 although in some basins, such as Dingjiagou and Phujym, the results were still
316 unsatisfactory. A possible reason for such a discrepancy is that the VIC model is unable
317 to capture the impact of human activities, such as reservoir regulations.

318 The streamflow values simulated using the parameters sets through the parameter
319 transfer scheme were validated over 9 basins based on the observations. Compared with
320 the calibration process, six validation basins covering two climate zones, such as Da
321 and Db, were used to examine the performance of the parameter transfer approach.
322 Overall, the validation results (Table 2) were consistent with the calibration statistics.



323 The R , NSE, and bias values for the validation period ranged from ~ 0.65 – 0.91 , ~ 0.31 –
 324 0.87 , and ~ 4.29 – 40.5% , respectively. The Zhangjiashan Basin had a relatively high bias,
 325 mainly because there were only two years of observation data available for validation.
 326 The best performance was found in the Hengshi Basin, while the worst was in the
 327 Chiling Basin.

328



329

330 **Figure 3: Monthly discharges for some calibrated basins. The stippled lines are**
 331 **observations, dashed lines are simulations from uncalibrated parameters, and**
 332 **the solid lines are simulations from calibrated parameters.**

333

334 **Table 2: Statistics of calibrated and validated monthly flows.**

| Location | Latitude | Longitude | Climate Zone | Period | R | NSE | Bias |
|----------|----------|-----------|--------------|--------|-----|-----|------|
|----------|----------|-----------|--------------|--------|-----|-----|------|



Calibration

| | | | | | | | |
|------------|-------|--------|----|-----------|------|------|---------|
| Yamadu | 43.62 | 81.8 | Bk | 2006-2008 | 0.91 | 0.59 | 7.59% |
| Dingjiagou | 37.55 | 110.25 | Bk | 1970-1986 | 0.47 | 0.26 | -20.70% |
| Bengbu | 32.93 | 117.38 | C1 | 1970-1986 | 0.82 | 0.65 | -2.78% |
| Tsuuang | 36.03 | 114.52 | C1 | 1970-1979 | 0.89 | 0.76 | -18.50% |
| Heishiguan | 34.71 | 112.93 | C1 | 1980-1982 | 0.91 | 0.72 | 25.40% |
| Jian | 27.1 | 114.98 | C2 | 1980-1982 | 0.86 | 0.75 | -4.86% |
| Ankang | 32.68 | 109.01 | C2 | 1980-1982 | 0.94 | 0.79 | 37.70% |
| Gongtan | 28.9 | 108.35 | C2 | 1980-1982 | 0.89 | 0.74 | -11.20% |
| Hoiyang | 23.17 | 114.3 | C3 | 1970-1982 | 0.92 | 0.74 | -3.54% |
| Wuzhou | 23.48 | 111.3 | C3 | 1970-1984 | 0.92 | 0.79 | 12.80% |
| Nanning | 22.8 | 108.36 | C3 | 1970-1983 | 0.87 | 0.74 | 13.60% |
| Shenyang | 41.46 | 123.24 | Da | 1970-1978 | 0.97 | 0.77 | 25.60% |
| Jilin | 43.88 | 126.53 | Da | 1980-1983 | 0.85 | 0.56 | -7.61% |
| Phujym | 45.1 | 124.49 | Da | 1977-1979 | 0.68 | 0.26 | 1.23% |
| Tsyamusy | 46.5 | 130.2 | Db | 1970-1978 | 0.86 | 0.69 | -3.84% |
| Shetang | 34.55 | 105.97 | Db | 1978-1988 | 0.78 | 0.58 | 12.40% |
| Maojiahe | 35.52 | 107.58 | Db | 1978-1982 | 0.84 | 0.61 | 28.60% |
| Yangcun | 29.3 | 91.96 | E | 1971-1975 | 0.88 | 0.6 | -6.77% |
| Changdu | 31.18 | 97.18 | E | 1975-1982 | 0.94 | 0.82 | 7.04% |
| Lasa | 29.63 | 91.15 | E | 1973-1975 | 0.93 | 0.81 | 5.26% |



Validation

| | | | | | | | |
|---------------|-------|--------|--------|-----------|------|------|--------|
| Zhangjiashan | 34.63 | 108.60 | Bk, Db | 1980-1982 | 0.91 | 0.67 | 40.5% |
| Zhanjiafeng | 40.37 | 116.47 | Da, Db | 1970-1979 | 0.85 | 0.69 | 4.29% |
| Dalinghe | 41.41 | 121.00 | Da, Db | 1970-1979 | 0.91 | 0.76 | -6.97% |
| Chiling | 42.20 | 123.50 | Da, Db | 1970-1979 | 0.71 | 0.31 | 9.85% |
| Luanxian | 39.73 | 118.75 | Da, Db | 1970-1983 | 0.91 | 0.79 | 9.69% |
| Haerbin | 45.77 | 126.58 | Da, Dc | 1970-1983 | 0.78 | 0.51 | -9.87% |
| Hengshi | 23.85 | 113.27 | C3 | 1976-1979 | 0.95 | 0.87 | 15.5% |
| Qianxinzhuang | 40.32 | 116.55 | Db | 2006-2014 | 0.65 | 0.34 | 6.90% |
| Boyachang | 40.40 | 116.65 | Db | 2006-2014 | 0.84 | 0.68 | 9.76% |

335

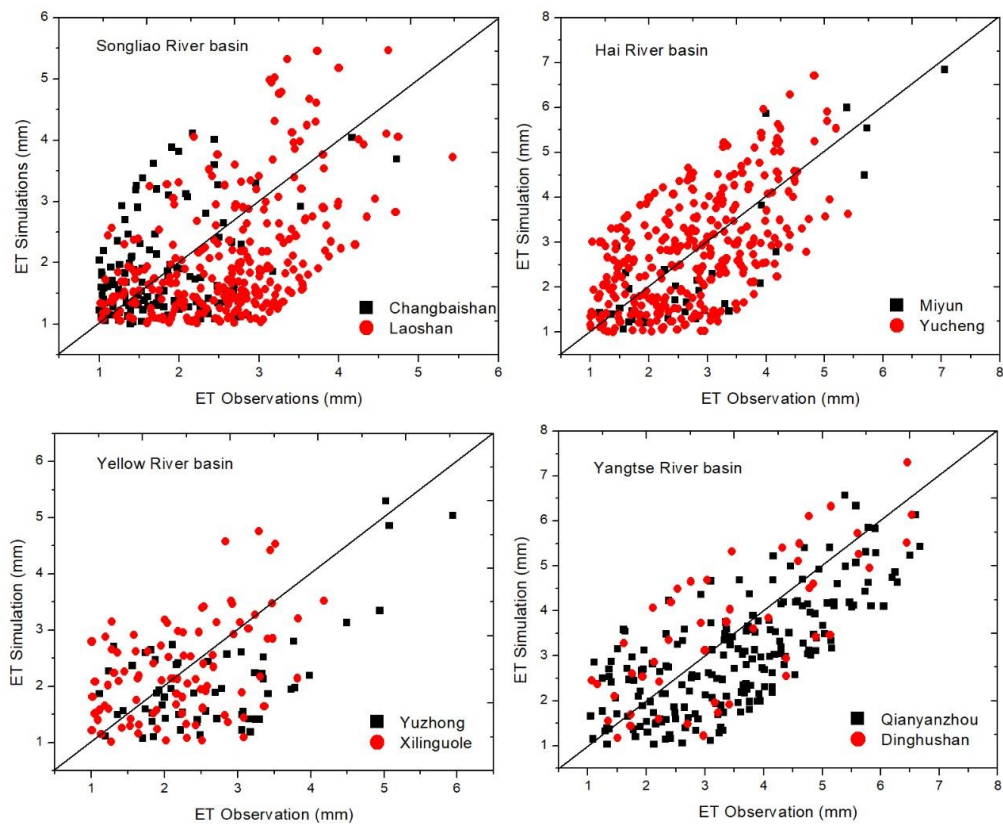
336 3.2 ET evaluation

337 The root mean square error (RMSE) is a widely used measure of the differences
 338 between model and observed variations (Yin et al., 2016). In this study, the RMSE was
 339 also employed to estimate the differences between VIC model simulations and in-situ
 340 observations. The statistics of the comparison between simulations and observations
 341 are shown in Fig. 4 and Fig. 5 provides a comparison of some selected stations in the
 342 four main basins (i.e., Songliao River Basin, Hai River Basin, Yellow River Basin and
 343 Yangtse River Basin). The VIC model performed well and showed reasonable
 344 consistency at the eddy covariance tower stations with respect to daily ET, with most R
 345 values being greater than 0.6. The average RMSE values ranged between 0.6 mm and
 346 3.6 mm. With respect to bias, many stations located in central China had values between



347 –60% and 20%. Weaker performances also occurred at a few stations mainly due to the
348 inconsistent scales of the two datasets, as the observation dataset includes single point
349 results, while model simulations are regionally averaged results. Therefore, the errors
350 may result from uncertainties in the in-situ measurements themselves and from
351 differences in the spatial scales between the model and the in situ measurements
352 (Gruber et al., 2013). As a whole, the strong relationships between ET simulations and
353 in-situ observations imply that they are qualitatively acceptable.

354 As for the spatial comparison of ET, Fig. 6 shows the seasonal changes and differences
355 between the VIC simulated ET and the GLASS ET. The VIC simulated larger ET values
356 in southeastern China and lower values for other areas relative to the GLASS products.
357 The differences ranged from –2 to 2 mm/day and this may have been caused by the
358 different temporal resolutions, which is 8 days for GLASS products. The average
359 difference for the four seasons was only approximately –0.36 mm, and thus the VIC
360 simulated ET was consistent with the RS estimated ET, implying an acceptable
361 performance for the model in this study.

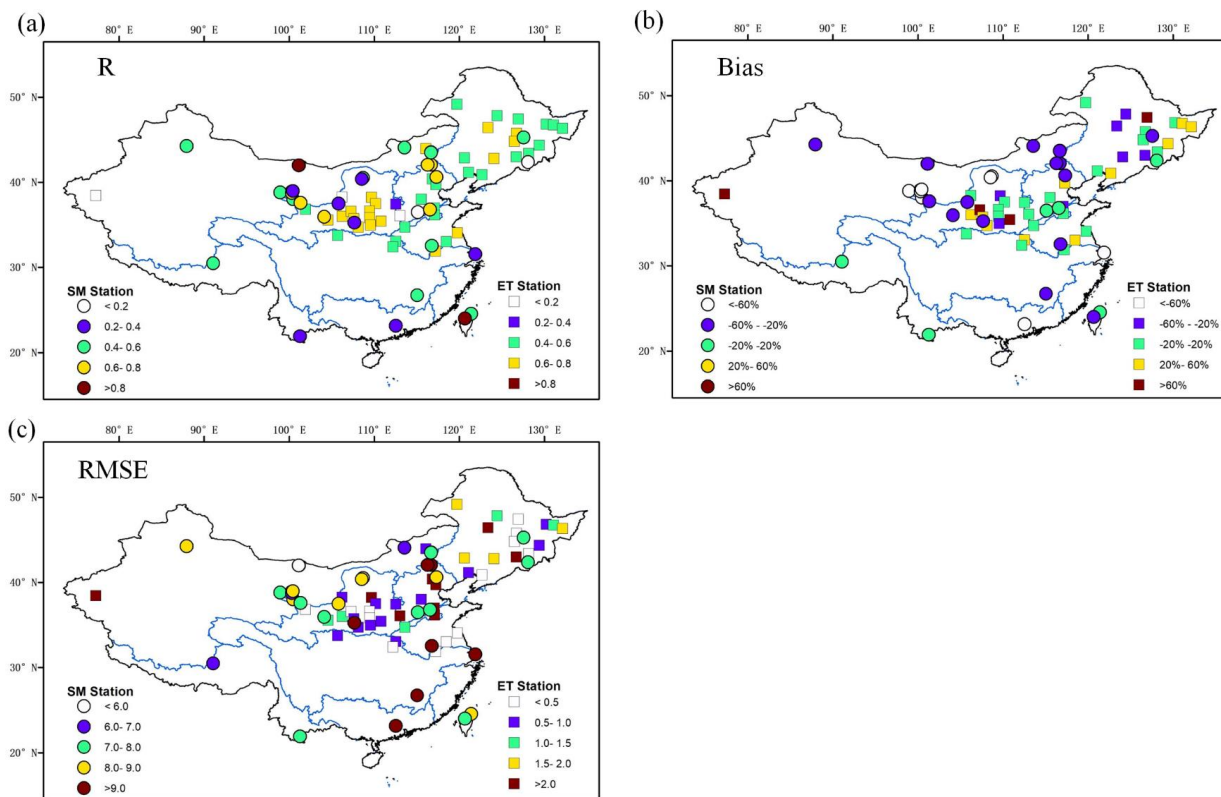


362

363 **Figure 4: Comparison of ET between observations and simulations of selected**

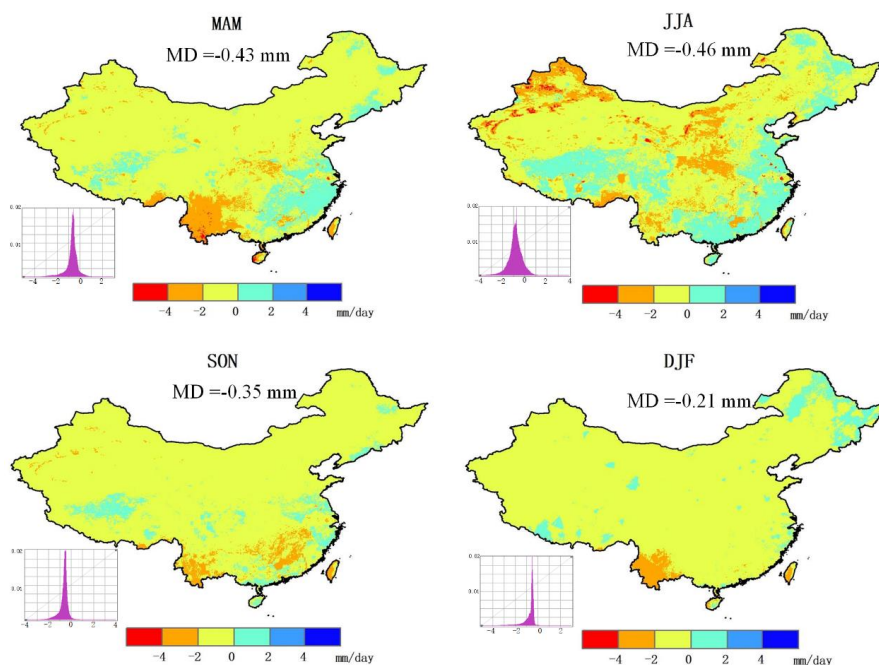
364

stations in four basins.



366 **Figure 5: Spatial distribution of the correlation coefficient (R), bias, and RMSE**

367 **between observations and simulations for ET and SM.**



368

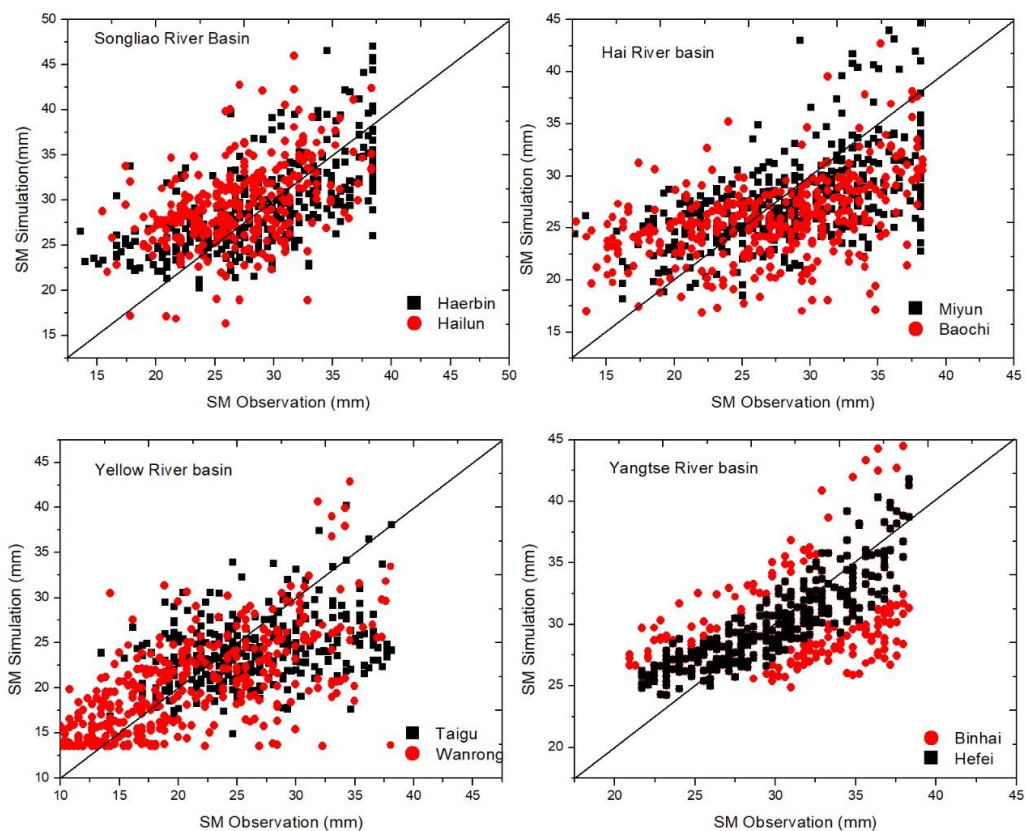
369 **Figure 6: Seasonal differences of ET between simulation and the GLASS for,**
370 **from top to bottom, spring, summer, autumn, and winter. MD is the mean**
371 **differences.**

372 3.3 SM evaluation

373 Figures 5 and 7 show the performance of the top 10-cm soil layer model estimates
374 against in-situ SM observations. As shown in Fig. 5, the R values for most stations were
375 higher than 0.6 and the RMSEs were less than 12 mm. There was a pattern that emerged
376 in which stations with a high R values (> 0.7) usually showed considerably low RMSEs,
377 indicating R and the RMSE are not independent indicators of SM. Although several
378 comparisons showed poor results, potentially because of the differences in temporal (10
379 days for observations and daily for simulations) and spatial resolutions. The stations
380 located in central China, such as the Yellow River Basin and Hai River Basin, tended



381 to have lower biases, ranging from -20% to 20% . Meanwhile, the rural stations had
382 larger biases, which may due to limited and/or inaccurate observation data. Overall, the
383 comparisons of the two SM datasets demonstrated that they matched reasonably well.
384 The ESA-CCI SM product was used to evaluate the SM results from spatial perspective.
385 Figure 8 describes the differences between model simulations and ESA-CCI results.
386 The important differences in winter (December–February) can be seen in southwestern
387 China, and reached more than 10 mm. The opposite pattern appeared in summer (June–
388 August), with high differences exhibited in southeastern China. Slight differences
389 between simulations and the ESA-CCI product were found in spring (March–May),
390 with high values in the Yangtze River Basin. In autumn (September–November), the
391 southern region was covered by high differences values, which is distinctly different
392 from northern China. Combined, these results indicate that the VIC model with properly
393 calibrated parameters provides satisfactory simulations of runoff, ET, and SM.

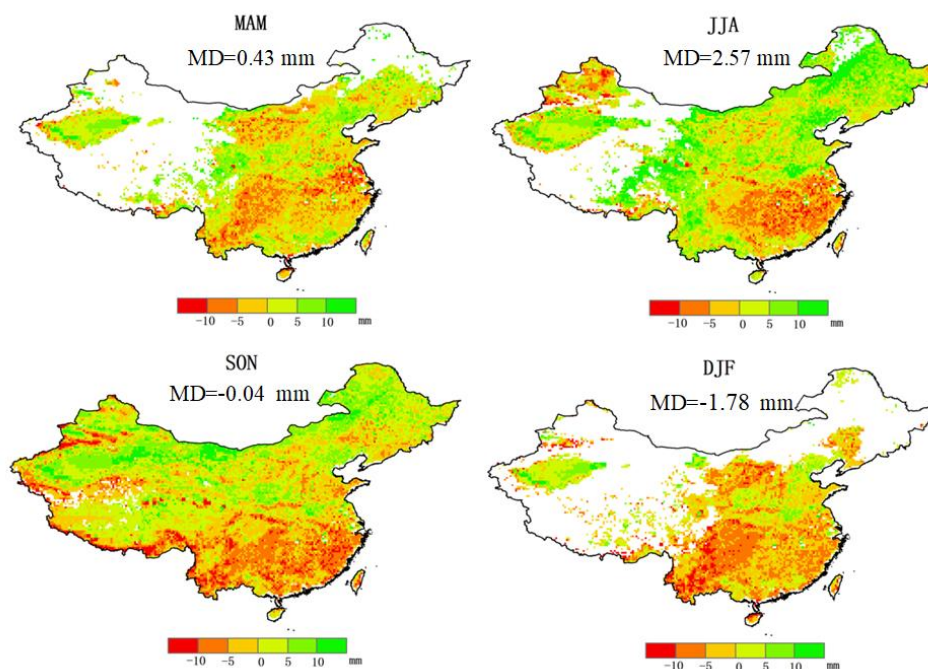


394

395 **Figure 7: Comparison between observations and simulations of selected stations**

396

in four basins.



397

398 **Figure 8: Seasonal distributions of differences between simulations and the ESA-**
399 **CCI cases for the 0-10 cm soil layer SM. From top to bottom for: spring,**
400 **summer, autumn and winter. MD is the mean differences.**

401

402 3.4 Application for detection of typical extreme events

403 Flood and drought are the main natural disasters that occur in China, and they have
404 become important restricting factors for the development of society, the economy, and
405 agriculture (Zhang et al., 2016). However, the lack of high-resolution data makes
406 identifying flash floods and droughts over short timescales (pentads or weeks) nearly
407 impossible (Zhang et al., 2017). It is also necessary to monitor flood and drought events
408 in small regions, especially for remote areas without sufficient and reliable observation



409 data. Therefore, reliable, high-resolution modeling is essential for better analyzing
410 historical and predicted extreme events and then to make informed decisions in flood
411 and drought management. In this study, we applied the simulated 0.0625° dataset to
412 analyze two typical extreme disasters that occurred during recent years in China and to
413 evaluate the potential of the modeling to detect drought and flood events.

414 **3.4.1 Beijing flood event of 2012**

415 On July 21, 2012, the heaviest rainfall over the past six decades lashed Beijing. An area
416 of ~16,000 km² and more than 1.6 million people were affected by the flood (Wang et
417 al., 2013). A few studies have focus on the causes and patterns of this heavy rainfall
418 (Huang et al., 2014; Liu et al., 2003), while little attention has been paid to the
419 associated hydrological processes, such as the generation of runoff.

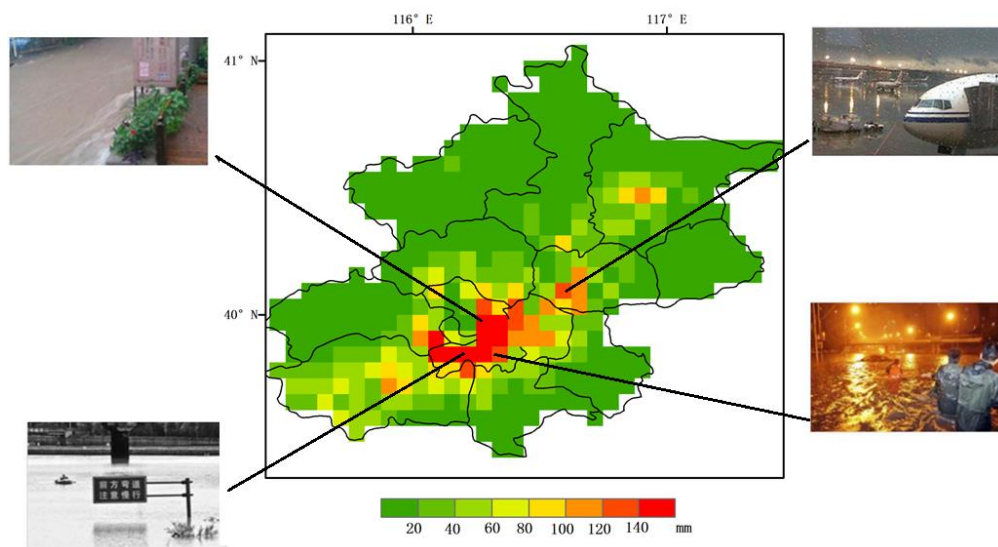
420 Here, we detected the flood coverage, which is represented by the runoff depth.
421 According to gauge observations, the intensive rainfall area extended from
422 southwestern Beijing to the northeastern areas (Chen et al., 2014). As shown in Fig. 9,
423 the runoff depth presented a SE–NE zonal distribution. However, the central region of
424 Beijing, which has the highest population and number of buildings, suffered the deepest
425 runoff, > 100 mm/day. This may have been due to the effects of urbanization during
426 recent years. There were four photos (Fig. 9) taken on July 21, 2012 that show the real
427 influence of this flood event (<http://www.weather.com.cn>).

428 To further evaluate the intensity of the flood event, we analyzed the frequency
429 distributions of precipitation and runoff (Fig. 10). The maximum precipitation was 287



430 mm over 24 hours, more than 50 mm of which was recognized as a rainstorm level in
431 76% of the area of Beijing. The mean precipitation is 103 mm on July 21, 2012.
432 Affected by the heavy rain, the maximum runoff is 172 mm; the average runoff is 26
433 mm for 24 hours. It should notice that the central urban area has the highest runoff
434 coefficient (Runoff/Precipitation) of 0.89, indicating that it will be at high flood risk
435 during urbanization when extreme rainfall happens (Wang et al., 2013).

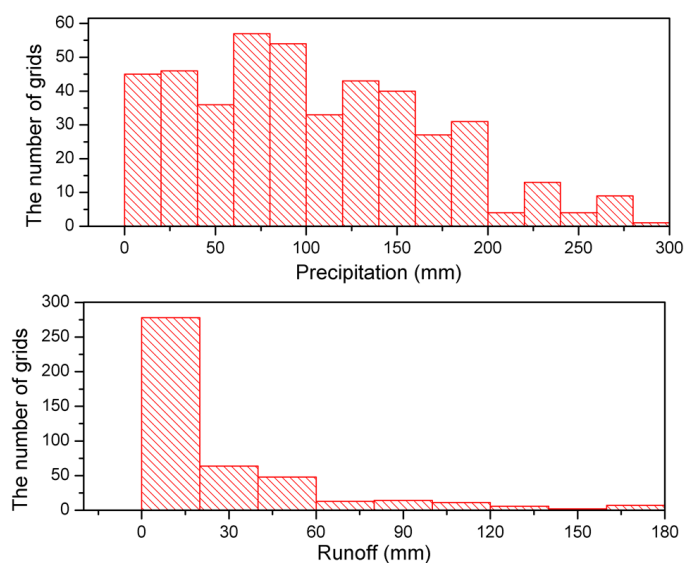
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437

438

Figure 9: Simulated runoff in Beijing on July 21, 2012



439

440 **Figure 10: Statistics of the numbers of grids with different precipitation and**
441 **runoff.**

442 3.4.2 North China drought event of 2009

443 From 2009–2010, a large-scale severe drought struck China (Ye et al., 2012). It lasted
444 for several months and subsequently has been considered as the most influential
445 drought event in northern and southwestern China (Zhu et al., 2018). In August 2009,
446 some portions of North China received only one inch of rainfall during the entire year.
447 In August of 2009, some portions of North China had received only one inch of rainfall
448 over the entire year.

449 As a result, this severe drought cost \$100 million worth of losses. In this study, the VIC-
450 simulated SM was used to assess the severity and extent of the drought, particularly
451 focusing on agricultural drought, which was defined as a SM deficit. To emphasize the
452 advantage of high-resolution modeling for drought detection, we conducted a coarse-
453 resolution modeling at a 0.25° resolution that had the same sources of meteorological



454 forcing and soil and vegetation parameters as the 0.0625° modeling so that the only
455 difference between the two simulations was the spatial resolution.

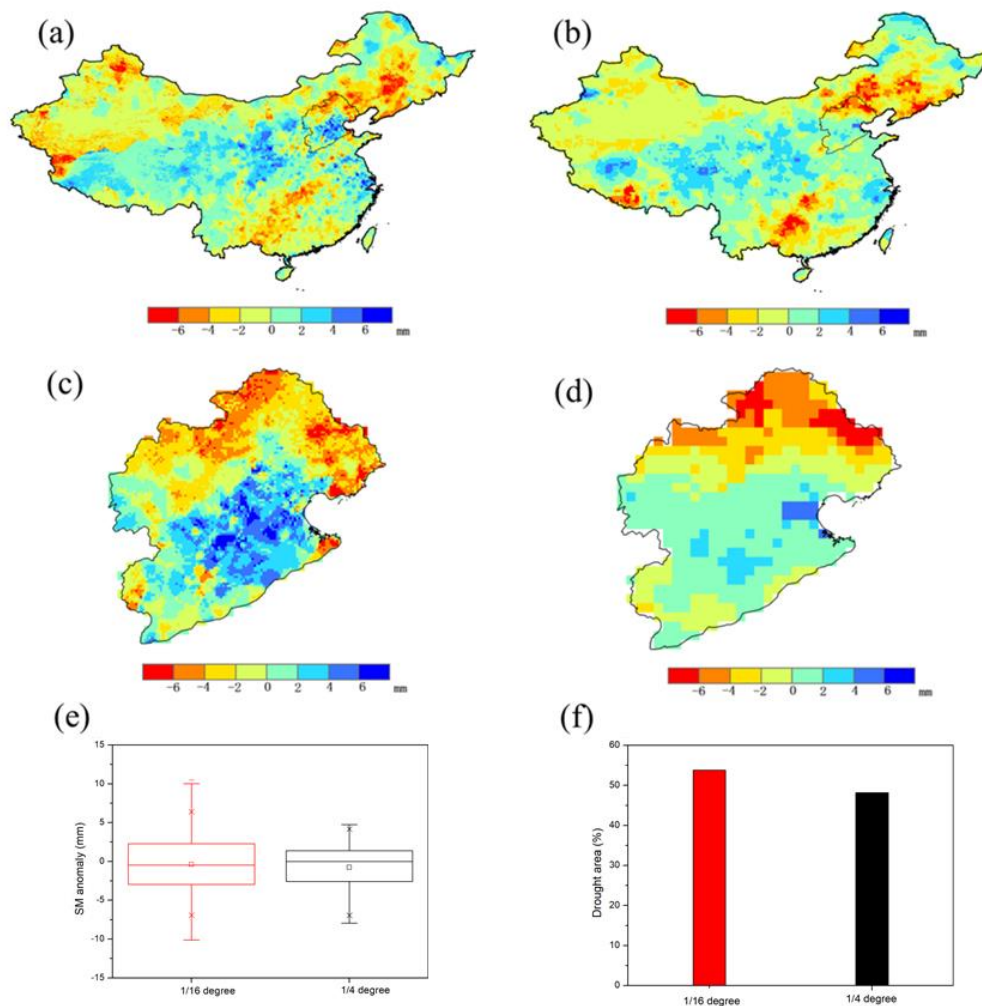
456 The simulated drought event patterns of the two simulations showed a SE–NE zonal
457 distribution. However, differences between the simulations were obvious. The severe
458 drought in the 0.0625° simulations extended over more areas in northwestern and
459 southern China than in the 0.25° simulations. The Hai River Basin was selected in order
460 to distinguish the regional differences between the two simulations. The Hai River
461 Basin is one of the largest basins in North China, and contains a large population of 137
462 million people (Qin et al., 2015). It has long been identified as being sensitive to climate
463 change and has a recorded history of decades long droughts events. As shown in Fig.
464 11(c) and (d), the SM anomaly shows more detailed spatial structures with the increased
465 spatial resolution of the simulation.

466 In the 0.0625° simulations, drought mainly existed in the northwestern and northeastern
467 regions, and a few southwestern areas were also affected; these results are similar to
468 those of Wu et al. (2015) , which were based on RS data with a 1-km resolution.
469 However, the 0.25° simulations cannot show a detailed drought distribution.

470 Additionally, the magnitude of the SM anomaly in 0.0625° simulation results was larger
471 than in the 0.25° results, which ranged from -10.12 mm to 10.50 mm and -7.94 mm
472 to 4.75 mm, respectively (Fig. 11e). In the two simulations, 53.79% and 48.13% of
473 areas were affected by drought (i.e., the percentages of the SM anomaly were less than
474 zero), as shown in Fig. 11(f). These results indicate that the 0.0625° simulation could
475 successfully capture detailed spatial distributions and the severity of drought events.



476 Based on these analyses, we also used the 0.0625° simulations to analyze agricultural
477 drought events in the Hai River Basin over the last 46 years. Figure 12 shows the SM
478 anomalies and durations of the agricultural droughts, which were calculated by the
479 percentage of days with negative SM anomalies in a year from 1970 to 2015. As for the
480 SM anomalies, ~50% of past 46 years have experienced drought events. Severe drought
481 events occurred in 1972, the 1980s, 1999, and 2006. Moreover, there were 36 years in
482 which the droughts had relatively long durations (i.e., they lasted more than six months),
483 especially in 2006, when more than 75% of days had negative SM anomalies. Therefore,
484 the Hai River Basin is a typical drought-prone region. It suffered several intensive and
485 long-term drought events between 1980 and 1985, and in 1999 and 2006, and these
486 findings are consistent with the conclusions of Qin et al. (2015).



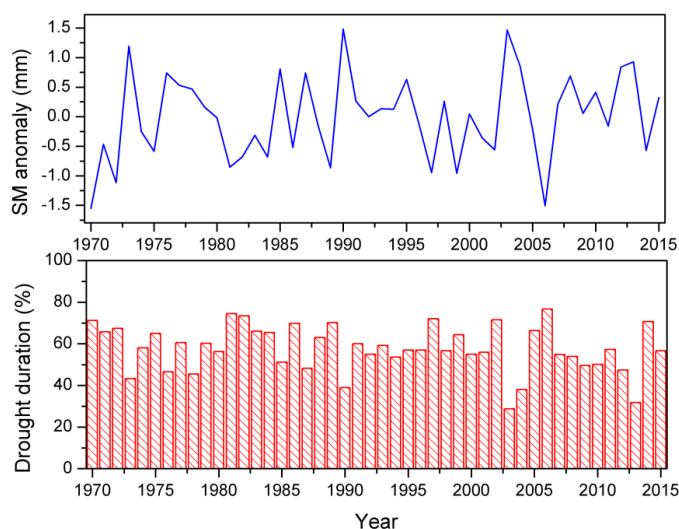
487

488 **Figure 11: Soil moisture anomaly from 0.0625° simulations in (a) China and (c)**

489 **the Hai River Basin, and from 0.25° simulations in (b) China and (d) the Hai**

490 **River Basin. The range of the (e) SM anomaly and (f) drought area of the Hai**

491 **River Basin from the two datasets are also shown.**



492

493 **Figure 12: Monthly SM anomaly and drought duration as a percentage of each**
494 **year from 1970 to 2015 in the Hai River Basin.**

495 **4. Discussion**

496 **4.1 Reliability of the modeling**

497 In this study, we developed a framework for the high-spatial resolution hydrological
498 modeling of runoff, ET, and SM at a 0.0625° spatial resolution across China from 1970–
499 2016. The model is highly reliable because, with respect to the forcing data, gridded
500 datasets were produced by interpolating station values from 2481 meteorological
501 stations across China, in contrast to the ~700 stations that have been commonly used in
502 many studies of China, such as that presented in the China Regional Surface
503 Meteorological Feature Dataset (CMFD). Meanwhile, high intensity station datasets
504 generally cover short periods of time, such as the CLDAS, which covered 2008–2016.
505 As for modeling process, a combination of climatic zones and river basin
506 methodologies was used to transfer the VIC parameters to uncalibrated areas. Soil



507 parameters, which are the most essential parameters of the VIC model, were adopted
508 from the newly released soil datasets of Dai et al. (2013) and Shangguan et al. (2013)
509 to improve the accuracy of hydrological modeling in our study. For model validation,
510 some previous studies have only validated runoff results using in-situ data (Lee et al.,
511 2017; Xie et al., 2007; Zhu and Lettenmaier, 2007), which may not guarantee the
512 reliability for other hydrological processes, such as ET and SM. In contrast, more
513 ground observations and RS data were used to validate simulations of runoff, ET, and
514 SM in our study.

515 Therefore, this high-quality, high-spatial resolution hydrological modeling could be
516 extended for relevant applications, such as detecting extreme events. As shown in Sect.
517 3.4, the simulations were capable of capturing detailed changes and providing reliable
518 information when drought and flood events occurred.

519 **4.2 Potential extension with China Land Data Simulation System (CLDAS) and** 520 **remote sensing (RS) data**

521 The CLDAS is a system that produces high-quality metrological forcing and SM
522 conditions over China at a 0.0625° resolution and in hourly time steps (Shi et al., 2011).
523 Three land surface models are included in the current version of the CLDAS-V2.0 (i.e.
524 CLM3.5, Noah-MP, and CoLM). In terms of the Global Land Data Assimilation System
525 (GLDAS) (Rodell et al., 2004) and the National Land Data Assimilation System
526 (NLDAS) (Mitchell, 2004), the VIC model is considered to fully simulate hydrological
527 processes.

528 In this study, the developed hydrological modeling framework based on VIC had the



529 same resolution as the CLDAS, and it was easy to couple with the CLDAS. Therefore,
530 this study provided an opportunity for the CLDAS to be combined with hydrological
531 modeling to better enhance its services.

532 Based on the high-quality and high-density drivers from the CLDAS, the simulation of
533 the VIC model could be applied to real-time hydrological process estimation across
534 China, and then offer an effective guide to detecting flood and drought events.
535 Furthermore, the RS data, such as LAI, albedo, and shortwave radiation, also could be
536 merged into the VIC, which may improve modeling results by considering the energy
537 balance.

538 **4.3 Limitations**

539 As shown in Sect. 3, the hydrological simulations were extensively validated with in
540 situ observations and RS data. However, with the exception of two stations, all of the
541 streamflow stations only had data records for the periods before 1990. The ET and SM
542 observations stations were mostly distributed in North China. Additionally, we
543 calibrated the most sensitive seven parameters of the VIC model (b , d_1 , d_2 , d_3 , D_{smax} ,
544 D_s , and W_s), while the other parameters were not calibrated. For example, the
545 wintertime LAI and canopy fraction has a strong influence on variations in the snow
546 water equivalent (Bennett et al., 2018). Therefore, further efforts are needed to improve
547 model parameters uncertainties and the accuracy and application of RS products, and
548 to enhance the support of ground-based observation networks.

549 This study improved the spatial resolution of hydrological modeling to ~6 km across
550 China, which is just one step toward further increasing the resolution. The modeling



551 needs to be improved to reach a so-called hyper-resolution (~1 km or finer), which is
552 one of the “grand challenges” in current hydrological research (Wood et al., 2011).
553 Moreover, as hydrological processes generally evolve over various temporal scales,
554 from minute to daily time steps, future studies should also increase the evaluation of
555 temporal resolutions simultaneously (Melsen et al., 2016). However, the modeling in
556 our study was conducted roughly, at a daily time step, alone due to the limitations of
557 the forcing data. Hourly or smaller time step data can capture more detailed processes,
558 such as flash floods, infiltration, and pore flow (Blöschl and Sivapalan, 1995).
559 Furthermore, the achievement of high-spatial and temporal-resolution modeling not
560 only requires the resolution to increase, but also involves the development of
561 hydrological models to consider hydrological processes that are consistent with such
562 high resolutions, including lateral groundwater flow (Zeng et al., 2018; Zeng et al.,
563 2016) and efficient runoff routing algorithms (Li et al., 2013; Meng et al., 2017; Wen
564 et al., 2012; Wu et al., 2014).

565 **5. Conclusion**

566 In order to address the fundamental questions associated with the effects of
567 environmental changes across various scales, we developed a high-resolution (0.0625°)
568 hydrological modeling for China using the VIC model over the period from 1970–June
569 2016.

570 The modeled runoff, ET, and SM were fully calibrated and validated against the data
571 from in-situ stations and RS. The modeled runoff results were significantly improved
572 after parameter calibration and transfer using a combination of climatic zones and river



573 basin methodologies. Additionally, the R and NSE values of most calibrated and
574 validated basins were greater than 0.70, and the relative bias was generally below 20%.
575 The simulations of humid regions, such as the Yangtze River Basin, tended agree better
576 with observations than those of arid regions. Furthermore, ET and SM simulations were
577 also validated against ground observations and RS products. The R and RMSE values
578 for ET and SM were quite acceptable. The simulated ET and SM and the RS products
579 (e.g., GLASS, ESA-CCI) were consistent across spatial and temporal distributions.
580 Therefore, the hydrological modeling is capable of capturing the hydrological processes
581 at such a high resolutions, and can provide reliable estimates of land surface
582 hydrological conditions in China.
583 Several important implications emerge from our work. For example, this
584 implementation has a higher spatial resolution and generally improved performance
585 relative to earlier model results (Lee et al., 2017; Zhang et al., 2014; Zhu and
586 Lettenmaier, 2007). The increased spatial resolution improves the ability of the
587 modeling to represent topographic effects and resolve smaller watersheds, and hence
588 provide information relevant to local water management concerns, such as on drought
589 and flood events.
590 Consequently, this is the first time that hydrological states and fluxes at a 0.0625° spatial
591 resolution have been produced for China, and they are freely available to analyze multi-
592 scale hydrological, ecological, and meteorological interactions and initial conditions.
593 Additional efforts will be needed to improve the hydrological modeling by using more
594 detailed model inputs and advanced parameter calibration techniques. Moreover, there



595 is great potential for the extension of our modeling results with CLDAS and RS data to
596 improve high-resolution modeling applications.

597 **Acknowledgements**

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601

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