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Effects of land use/cover change on atmospheric humidity in three urban agglomerations in the Yangtze River Economic Belt, China

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1 **ABSTRACT**

2 Land use/cover change (LUCC) affects regional climate not only through its direct
3 changes of land surface properties, but also through its further modifications of
4 land-atmosphere interactions. Urban land expansion is a typical case of LUCC in
5 highly populated areas, and has been widely discussed about its impacts on regional air
6 temperature, notably known as urban heat island (UHI) effects. Besides air temperature,
7 atmospheric humidity, as another key variable in hydrometeorology and climate, would
8 be inevitably affected by LUCC as well. However, the impacts of LUCC on
9 atmospheric humidity seem to have not been investigated as much as on temperature.
10 We examined atmospheric humidity changes by trend analyses of humidity indicators
11 in three representative urban agglomerations in the Yangtze River Economic Belt
12 (YREB), China during 1965-2017, and found the evident urban dry island (UDI)
13 effects which are characterized by significant humidity decrease and vapor pressure
14 deficit increase. In different urban cores, the severity levels of UDI are different.
15 Furthermore, strong positive correlations between humidity and evapotranspiration,
16 and between evapotranspiration and leaf area were detected during 2001-2017 when
17 cities entered the accelerated stage of land expansion, indicating that LUCC affects
18 regional climate through an ecohydrological way. We speculated that the UDI effect
19 will not appear until urban land expands to a certain scale. Besides, the UHI effect
20 emerged in the early stage of urban expansion, about 5 years earlier than the UDI
21 effect, and has not performed prominently in recent years. This implies that
22 urbanization-induced LUCC may exert a larger influence on UDI than on UHI in the
23 current later period of urban expansion.

24 **Keywords:** Land use/cover change; Atmospheric humidity; Evapotranspiration; Urban
25 dry island; Remote Sensing

26

27 **1 Introduction**

28 Land use/cover change (LUCC) affects local and regional climate not only through
29 its direct changes of land surface radiative, biophysical and aerodynamic properties
30 such as albedo and roughness, but through further modifications of land-atmosphere
31 interactions which incorporate the surface energy budget, water cycle and carbon cycle
32 (Betts et al., 1996; Boisier et al., 2012; Foley et al., 2005; Ma et al., 2019; Rigden and
33 Li, 2017; Pielke et al., 2011). Urbanization as one of most typical cases of LUCC in
34 highly populated areas, is characterized by the rise of impervious surfaces at the cost of
35 vegetated and evaporating soil surfaces, which triggers a series of consequences on
36 regional climate (Clinton and Gong, 2013; Li et al., 2020; Song et al., 2018; Zhou et al.,
37 2016). The most well recognized and discussed effect is urban heat island (UHI) which
38 depicts warmer urban areas than its surroundings, and it is generally attributed to
39 changes in surface radiative heating and surface energy redistribution (Arnfield, 2003;
40 Li et al., 2019; Logan et al., 2020; Oke, 1982; Taha, 1997; Zhou et al., 2014). Closely
41 accompanying UHI, another less discussed but equally important urbanization effect
42 on regional climate is urban dry island (UDI) which describes that urban areas have
43 lower atmospheric humidity than its surroundings (Akinbode et al., 2008; Landsberg
44 and Maisel, 1972; Lokoshchenko, 2017).

45 Researches have already displayed different consequences of UDI. Numerical
46 simulations and statistical analysis found that UDI could mitigate urbanization effect
47 on warming through compensating for the impact of anthropogenic aerosols on
48 downward longwave radiation, because UDI could decrease urban cloud cover due to
49 more mixing of water vapor in the boundary layer and less convective available
50 potential energy (Du et al., 2019; Zhang et al., 2009). Furthermore, UDI could improve
51 human thermal comfort to some extent under UHI, because perceived heat stress was
52 stronger when relative humidity was higher under given temperature and people would
53 tend to be more sensitive to changes in humidity than to changes in temperature at high
54 temperatures (Barradas, 1991; Gaffen and Ross, 1999; Hondula et al., 2017; Luo and

55 Lau, 2018). However, UDI could also slow down the water vapor to reach its
56 saturation and extend the life time of dust, smoke and particulate matters suspending in
57 the air, making it difficult for the haze particles to transform into fog drops and
58 subsequently leading to lower horizontal visibility (Ding and Liu, 2014; Gultepe et al.,
59 2007). A higher water demand for irrigation of urban ecosystem would also emerge
60 due to the increase of potential evapotranspiration caused by drying urban boundary
61 layer atmosphere (Yang et al., 2017). Therefore, it is of great societal concerns to
62 explore both the temporal-spatial patterns of UDI and its drivers behind so as to
63 understand more aspects of urbanization effects on regional climate.

64 Previous literatures related to UDI mainly focused on the description of the
65 phenomenon, its temporal and spatial patterns and superficial causes. Based on the
66 findings that vapor content had diurnal and seasonal cycles, lower humidity of urban
67 areas than that of rural areas during daytime was attributed to temperature rise and ET
68 reduction in cities while nighttime opposite phenomenon was attributed to enhanced
69 dewfall in the countryside and higher temperature of night urban air which had the
70 potential to contain more water vapor (Hage, 1975; Landsberg and Maisel, 1972;
71 Moriwaki et al., 2013). Generally, humidity differences between urban and rural areas
72 were negative during the summer, while positive ones were found in winter and were
73 related to urban combustion sources of water vapor, urban snowmelt on occasions
74 when rural temperatures were below freezing and the seasonal features of the wind
75 (Ackerman, 1987; Moriwaki et al., 2013). Spatial patterns of UDI within cities were
76 related to urban topography and geometry, vegetation cover of park and garden areas,
77 and the frequency and intensity of the wind (Cuadrat et al., 2015; Yang et al., 2017).

78 Despite the identification of UDI characteristics, only very few researches have
79 thought of it as a consequence of urbanization-induced LUCC in addition to other
80 kinds of human activities and investigated the corresponding underlying mechanisms
81 (Boisier et al., 2012; Luo and Lau, 2019; Pielke et al., 2011). Urban land expansion
82 carries on majorly at the expense of rural lands used for agriculture and forestry, which

83 leads to lower rates of evapotranspiration (ET; Boggs and Sun, 2011; Sun and Lockaby,
84 2012). Generally recognized as a major moisture source of atmospheric humidity as
85 well as a major contributor to UDI, ET is a key hydrometeorological variable uniquely
86 linking the energy cycle and the water cycle and found to be controlled by both
87 climatic factors and LUCC (Fisher et al., 2017; Li et al., 2017; Tan et al., 2014;
88 Odongo et al., 2019). Thus, it is rational to relate LUCC (i.e., leaf area index [LAI]) to
89 the coupling of hydrological (i.e., ET) and meteorological (i.e., air temperature and
90 humidity) processes, in order to better understand UDI in the interactions between
91 ecohydrological processes and urban climate feedbacks (Bronstert et al., 2002; Hao et
92 al., 2018; Sun et al., 2011).

93 After the initial urban transition stage between 1950 and 1980, China is now in its
94 late period of the accelerated stage between 1980 and 2030 (Farrell and Westlund,
95 2018). The urban built-up areas of the nation have gained from 6720 km² in 1981 to
96 56075.9 km² in 2018, with an average annual growth rate of 5.902% (Ministry of
97 Housing and Urban-Rural Development of the People's Republic of China, 2020).
98 Relying on the abundant natural resources of the Yangtze River Basin, the Yangtze
99 River Economic Belt (YREB), a key zone supporting the sustained growth of economy
100 of the nation, takes the lead in the urbanization development. Meanwhile due to
101 differences in natural resources and economic development, there are obvious temporal
102 and spatial differences in the urbanization process of urban agglomerations in the upper,
103 middle and lower reaches of the Yangtze River. Therefore, selecting areas with obvious
104 but varying degrees of urban expansion processes for comparative research and
105 analysis can reflect the differences in the impacts of urbanization processes on regional
106 climate changes to some extent.

107 In this study, three representative urban agglomerations with different levels of
108 urbanization along the Yangtze River was examined for their atmospheric humidity
109 changes and trends, so as to detect the potential effects of rapid urban expansion on
110 local and regional climate, specifically UDI development. Correlation analyses was

111 performed between the pairs of atmospheric humidity indicators and ET, atmospheric
112 humidity indicators and temperature and ET and LAI, intending to explain the
113 mechanisms how urbanization affects local and regional climate through
114 ecohydrological processes. Our results may spark insights into future urban planning
115 and landscape design in mitigating climate change and maintain sustainable
116 development, and more quantitative estimations of urban expansion effects on local
117 and regional drying trends are needed especially when urbanization development
118 reaches to a certain scale.

119 **2 Data and Methods**

120 *2.1 Study Area*

121 The study areas include three national-level urban agglomerations in the Yangtze
122 River Economic Belt (YREB; Fig. 1): the Yangtze River Delta urban agglomeration
123 (YRDUA), the midstream urban agglomeration (MUA) and the upstream urban
124 agglomeration (UUA). The boundaries of the three urban agglomerations as well as
125 urban cores are identified by administrative divisions from National Development and
126 Reform Commission of China. Sites located in areas with much less built-up lands are
127 selected as representative rural sites. More basic information of the study areas is
128 shown in Table 1.

129 <Fig. 1>

130 <Table 1>

131 The YREB is located in the central and southern part of the nation and extends
132 from Shanghai in the east to Yunnan in the west, covering 11 provinces with an area of
133 approximately 2.05 million km². Located in the subtropical monsoon region and with a
134 relatively low latitude, the YREB has a relatively large amount of solar radiation. The
135 northerly wind prevails in winter and the southerly wind prevails in summer. In
136 addition to these common geographical and climatic conditions, there also lies some
137 differences among the three urban agglomerations. YRDUA is located in the lower

138 reaches of the Yangtze River, bordering the Yellow Sea and the East China Sea, at the
139 intersection of the river and the sea. The Taihu Plain is the main body of YRDUA.
140 MUA connects the east to the west, the south to the north and includes the Jiangnan
141 Plain, the Dongting Lake Plain and the Poyang Lake Plain. UUA is located in the
142 Sichuan Basin. It is divided into Chengdu Plain, central Sichuan hills and parallel ridge
143 valleys in eastern Sichuan. The mountainous area around the enclosed basin is
144 relatively low in the southeast, which is favorable for the entry of water vapor. The
145 relatively high mountainous area in the northwest is not conducive to the loss of water
146 vapor, resulting in high air humidity, rainy and foggy weather, less sunshine and low
147 wind speed.

148 In the early 1990s, YRDUA was well ahead in the process of urbanization after
149 Pudong Development and Opening-up started. Then UUA and MUA began to emerge
150 when “Four Alongs” Open Development Strategy was proposed. The proposal and
151 implementation of the West China Development in 1999 and the Central Rising
152 Strategy in 2006 led to rapid growth of UUA and MUA, respectively. In 2014, the
153 “Guiding Opinions on Promoting the Development of the YREB by Relying on
154 Golden Waterways” and the “Plan of the Comprehensive Three-Dimensional
155 Transportation Corridor of the YREB (2014-2020)” was released to promote the
156 synergistic development of the three urban agglomerations.

157 <Fig. 2>

158 Urban built-up areas reflected by impervious surfaces show obvious urban land
159 expansion around core cities in all three urban agglomerations, especially in YRDUA
160 (Fig. 2a, 2c and 2e). At the beginning of economic reform in China in 1978, the
161 percentage of impervious surface in YRD, MUA and UUA is 0.641%, 0.055% and
162 0.048%, respectively, while by the time of 2017, the number changes into 11.768%,
163 2.413% and 1.956%, respectively (Fig. 2b, 2d, and 2f). Urban impervious surface in
164 YRD first increased at a lower rate of 0.10% every year from 1978 to 2000, and then
165 surged at the speed of 0.55% every year after 2000. Neither MUA nor UUA showed

166 obvious changes in impervious surface from 1978 to 2000, while they both began to
167 expand built-up areas after 2000, at not very high rates similar to the first increasing
168 stage of YRDUA. These differences in urban expansion processes imply that
169 urbanization effects on local and regional climate in YRDUA probably have begun to
170 take form, while MUA and UUA have just experienced the initial subtle impacts of
171 urbanization. Therefore, it is rational to compare changes of local climate conditions of
172 these three urban agglomerations in order to advance understanding of effects of
173 different levels of urbanization.

174 *2.2 Regional ET, LAI and Impervious surface area*

175 The improved MOD16A2V006 Moderate Resolution Imaging Spectroradiometer
176 (MODIS) dataset, providing global actual evapotranspiration (*ET*) estimates with a
177 resolution of 8-day and 500-m from 2001 to 2017 (Running et al., 2017), was acquired
178 to explore *ET* and its changes of urban agglomerations. Leaf area index (*LAI*) used
179 to assess vegetation cover changes was acquired from MOD15A2HV006 dataset also
180 with a resolution of 8-day and 500-m from 2001 to 2017 (Myneni, et al., 2015). These
181 two MODIS products were then batch processed by MODIS Reprojection Tool and
182 ArcGIS to obtain annual mean *LAI* and annual *ET* of the study area. The 40-year
183 (1978-2017) continuous and consistent impervious surface distribution data in 30-m
184 resolution in China (Gong et al., 2019) was employed to reflect urban built-up land
185 expansion scales of the study area.

186 *2.3 Climate Data*

187 The daily meteorological data was acquired from 187 standard weather stations
188 across YRD, MUA, and UUA (59, 86 and 42, respectively) for the period of
189 1965-2017. Obtained from the China Meteorological Administration, the
190 meteorological data which included daily mean relative humidity (*RH*, %),
191 atmospheric pressure (*pres*, kPa), and daily maximum and minimum near-surface air

192 temperature (T_{\max} , T_{\min} and °C), was employed to calculate atmospheric indicators
 193 (i.e., actual vapor pressure (e_a), specific humidity (q) and vapor pressure deficit
 194 (VPD)) through a series of empirical formulas. After calculation at the station level,
 195 Ordinary Kriging Interpolation Algorithm (Matheron, 1963) was applied to interpolate
 196 the stational meteorological data into grid data with a 500-m spatial resolution in
 197 accordance to the resolution of MODIS-derived datasets, so as to further investigate
 198 regional climate changes.

199 2.4 Humidity Indicators

200 A number of humidity variables can be employed to reflect atmospheric humidity
 201 considering different purposes (Song et al., 2012). In order to investigate both water
 202 vapor content and the moist degree of the atmosphere, herein four humidity indicators
 203 were examined: RH , q , e_a and VPD . Saturation vapor pressure indicating the
 204 ability of the air to hold moisture, can be calculated from the air temperature (Allen et
 205 al., 1998):

$$206 \quad e^o(T) = 0.6108 \exp \left[\frac{17.27T}{T + 237.3} \right] \quad (1)$$

207 where $e^o(T)$ is saturation vapor pressure (kPa) at the air temperature T (°C).

208 The mean saturation vapor pressure (e_s , kPa) for a day is computed as the mean
 209 between saturation vapor pressure at daily maximum temperature (T_{\max} , °C) and daily
 210 minimum air temperature (T_{\min} , °C):

$$211 \quad e_s = \frac{e^o(T_{\max}) + e^o(T_{\min})}{2} \quad (2)$$

212 Actual vapor pressure (e_a , kPa) is calculated as the mean saturation vapor pressure
 213 (e_s , kPa) multiplied by measured daily mean relative humidity (RH , %):

214
$$e_a = e_s \times RH \quad (3)$$

215 Vapor pressure deficit (*VPD*, kPa) representing the atmospheric moisture demand
 216 is defined as the difference between e_s and e_a :

217
$$VPD = e_s - e_a \quad (4)$$

218 Specific humidity (q , g/g) is the ratio of the mass of water vapor to the total mass
 219 of the moist air parcel:

220
$$q = \frac{0.622e_a}{pres - 0.378e_a} \quad (5)$$

221 where *pres* is the atmospheric pressure (kPa).

222 *2.5 Trend and Change Point analyses*

223 First the simple linear regression analysis was employed to detect the trends of
 224 atmospheric humidity indicators at the pixel level. The slope of the linear fitted lines
 225 represents the direction and extent of the trend. Then the significance of the trend was
 226 evaluated by the non-parametric Mann-Kendall (MK) test (Kendall, 1975; Mann,
 227 1945). The MK test is based on the test statistic S defined as:

228
$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (6)$$

229 where x_i is the sequential data value at time i , n is the length of the dataset, and

230
$$\text{sgn}(x_j - x_i) = \begin{cases} 1 & x_j > x_i \\ 0 & x_j = x_i \\ -1 & x_j < x_i \end{cases} \quad (7)$$

231 When n is larger than 10, the statistic S is approximately normally distributed
 232 with the mean and variance as:

233
$$E(S) = 0$$

234
$$Var(S) = \frac{1}{18} \left[n(n-1)(2n+5) - \sum_{k=1}^m t_k(t_k-1)(2t_k+5) \right] \quad (8)$$

235 where m is number of tied groups and t_k is the number of records in the k th tied
 236 group. The standardized test statistic Z is calculated as:

237
$$Z = \begin{cases} \frac{(S-1)}{\sqrt{Var(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{(S+1)}{\sqrt{Var(S)}} & S < 0 \end{cases} \quad (9)$$

238 The null hypothesis that there is no trend would be rejected if the absolute value of
 239 Z is larger than $Z_{1-\alpha/2}$, where $Z_{1-\alpha/2}$ is the upper $\alpha/2$ quantile of the standard
 240 normal distribution.

241 A divisive hierarchical estimation algorithm for multiple change point analysis was
 242 employed at the station level to identify the significant humidity and air temperature
 243 change points of core cities. This method is based on Euclidean distance between the
 244 sample observations. Let $x_1, x_2, \dots, x_n \in x^d$ be an independent sequence of
 245 observations, where x_n is the independent and integrated (*iid*) observations in time
 246 n . Then there is a single hypothesized change point location τ , in which
 247 $x_1, \dots, x_\tau \stackrel{iid}{\sim} F_1$ and $x_{\tau+1}, \dots, x_n \stackrel{iid}{\sim} F_2$. The homogeneity in distributions is tested with the
 248 null hypothesis of $F_1 = F_2$. Further this approach is extended to a nonparametric
 249 technique named E-Divisive that can simultaneously identify both number and location
 250 of change points of a sequence of multivariate observations without any prior
 251 assumption (Matteson and James, 2014; James and Matteson, 2014). The statistical
 252 significance of the E-Divisive is determined by a permutation test under the null
 253 hypothesis of no additional change point.

254 *2.6 Correlation analysis*

255 The Pearson's correlation analysis (Pearson, 1895) was performed for key variables
256 at the pixel level between the pairs of *RH* and *ET*, *q* and *ET*, *e_a* and *ET*,
257 *VPD* and *ET*, *RH* and air temperature (*TEM*), *ET* and *LAI*. The Pearson's
258 Correlation Coefficient (*r*) is calculated as:

$$259 \quad r = \frac{1}{n} \sum_{i=1}^n \left[\left(\frac{x_i - \bar{x}}{S_x} \right) \left(\frac{y_i - \bar{y}}{S_y} \right) \right] \quad (10)$$

260 where *n* is the size of time series, *x_i* and *y_i* are the observed values, \bar{x} and \bar{y}
261 are mean value of observed values, *S_x* and *S_y* are standard deviations. The
262 significance of *r* is determined by *t*-test. According to both *r* and the significance
263 level, there are three types of correlation in this study: “Significantly positive
264 correlation” with *p* < 0.1, “Significantly negative correlation” with *p* < 0.1, and
265 “Nonsignificant correlation” with *p* > 0.1.

266 **3 Results and Discussion**

267 First the observed annual mean *RH* of core cities and their surrounding rural
268 areas at the station level were explored to find out if there were apparent changes of
269 atmospheric humidity. Then more humidity indicators were calculated and the station
270 meteorological data were interpolated into grid data so as to check the regional patterns
271 of humidity changes. At last, the explanation and underlying mechanisms for humidity
272 changes were examined and discussed.

273 *3.1 The Appearance of UDI 5 years after UHI*

274 The station level data of annual mean *RH* and air temperature (*TEM*; Fig. 3, 4
275 and 5) of core cities and rural areas in the three urban agglomerations (Fig. 1b-d) was
276 detected by non-parametric multiple change point analysis. The results suggest that

277 there was a common significant change point of *TEM* with $p < 0.05$ at around
278 1995 in almost all stations, no matter urban or rural ones. Before the change point,
279 *TEM* significantly increased at a high rate, and after 1995, *TEM* begun to fluctuate
280 without obvious rise or fall. These results proved the warming trend and the time
281 period of significant *TEM* rise, i.e., before 2000, which suggests that *TEM* rise
282 happened before rapid urbanization as discovered in Fig. 2. Meanwhile, relatively
283 small but almost simultaneous warming of rural areas compared to core cities further
284 implies that urbanization may not be the major contributor to the appeared UHI effect,
285 consistent with the former researches (Sun et al., 2016; Zhou et al., 2014).

286 The common significant change point of *RH* in core cities with $p < 0.05$ was
287 at around 2000, while almost no significant change point was found in the rural areas.
288 This indicates that core cities went through significant *RH* decline at different levels
289 after 2000 when urban expansion came into the accelerated stage, while *RH* in rural
290 areas did not display obvious changes. Since significant changes in *TEM* precede
291 *RH*, the UHI effect occurred generally previous to the UDI effect for about 5 years.
292 Considering that the rapid expansion of urban impervious surface took place only after
293 2000 when *RH* begun to decrease while *TEM* remained stable, it is fair to infer
294 that the impact of LUCC on UDI is superior to that on UHI. Urban lands with more
295 impervious surface instead of vegetation cover, simultaneously working with other
296 factors such as anthropogenic aerosols and greenhouse gases, might reduce surface
297 radiative heating, which is first and predominantly balanced by reduction in the latent
298 heat flux (i.e., evapotranspiration) and then the sensible heat flux (Dhara, 2020; Liepert
299 et al., 2004; Miller et al., 2004; Taha, 1997; Wild et al., 2004). Thus,
300 urbanization-induced LUCC may have a larger influence on evapotranspiration and
301 thereby on the atmospheric humidity above the ground, and then the UDI effect
302 appears.

303 <Fig. 3>

304 <Fig. 4>

<Fig. 5>

305

306 3.2 Regional UDI Patterns

307 The regional RH trend of YRDUA suggests that the whole region has
308 experienced decreasing RH at different levels during 1965-2017 (Fig. 6a). Regional
309 mean annual RH decreased at the rate of 0.980% per decade, while the drying trends
310 were most significant in the central and eastern areas with a maximum decreasing
311 speed of 2.396% per decade. The decreasing trends of RH in the northern and
312 western areas were relatively smaller. The regional disparities of RH trend followed
313 a quite similar spatial distribution pattern of impervious surfaces (Fig. 2a), implying
314 that this phenomenon may be an effect of urban expansion. The station level data (Fig.
315 3) detected by non-parametric multiple change point analysis further suggests that
316 there was a common significant change point of RH with $p < 0.05$ at around 2003
317 in all three core cities (i.e., Nanjing, Shanghai, and Hangzhou), which means that RH
318 started to decrease sharply after 2003 while just fluctuated mildly before 2003.
319 Meanwhile RH in areas with lagged urbanization almost stayed unchanged with
320 modest fluctuation except Sheyang where significant but relatively small RH
321 decrease of 0.340% per decade was found (Table 2). The trends of the other three
322 humidity indicators (Fig. 6b-d) once more confirmed the drying climate and its
323 regional changing disparities in the region (maximum rates of -0.110 g/kg per decade,
324 -0.179 hPa per decade and 0.720 hPa per decade for q , e_a and VPD , respectively).
325 More noticeably, associated with urban expansion and connectivity development, a dry
326 island cluster instead of isolated dry islands has formed, mainly centered on core
327 mega-cities, agreeing with the former studies (Hao et al., 2018; Luo and Lau,2019).

<Fig. 6>

328

<Table 2>

329

330 The regional RH trend of MUA shows that most areas have undergone different
331 levels of RH decline except the western fringe, during 1965-2017 (Fig. 7a). Regional

332 mean annual RH decreased at the rate of 0.646% per decade. The most obvious
333 decreasing rate of RH was found in the west-central and eastern Nanchang areas,
334 and reached as high as 1.977% per decade. The spatial distribution pattern of RH
335 trend was related but not completely similar to the distribution of impervious surfaces
336 (Fig. 2c). The station level data (Fig. 4) further shows that RH in Wuhan dropped
337 sharply after 1995 and then started to rebound after 2004, back to almost the levels of
338 1990s after 2010. RH in the other two core cities, i.e. Nanchang and Changsha, both
339 decreased obviously at about 2005, and then has rebounded to varying degrees in
340 recent years. RH in the surrounding rural areas, i.e., Nanzhang, Lushan and Nanyue,
341 remained almost unchanged for all the years and no significant change point was
342 detected (Fig. 4, Table 2). The regional variation of trends of the other three humidity
343 indicators (Fig. 7b-d) were slightly different but generally consistent with that of RH .
344 The maximum changing rates was -0.139 g/kg per decade, -0.248 hPa per decade and
345 0.588 hPa per decade for q , e_a and VPD , respectively.

346 <Fig. 7>

347 The regional RH trend of UUA shows that areas with intensive human activities
348 has gone through different levels of RH decline during 1965-2017 (Fig. 8a).
349 Regional mean annual RH decreased at the rate of 0.654% per decade, and the
350 drying trend was most obvious in northern Chengdu and its surrounding areas with a
351 maximum decreasing speed of 1.982% per decade. The station level data (Fig. 5)
352 further shows that after 2001, RH in Chengdu first declined obviously, and then has
353 rebounded a little in recent years, while RH in Chongqing only displayed decreasing
354 trend after 2010. RH of Nanbu and Naxi in the surrounding areas with lagged
355 urbanization almost remained unchanged or displayed unobvious downward
356 fluctuation (Fig. 5, Table 2). The regional variation of trends of the other three
357 humidity indicators (Fig. 8b-d) were slightly different but generally consistent with
358 that of RH . The maximum changing rates was -0.125 g/kg per decade, -0.211 hPa per
359 decade and 0.582 hPa per decade for q , e_a and VPD , respectively.

360 <Fig. 8>

361 Abovementioned regional and station levels analyses of atmospheric humidity
362 indicators suggest that the distribution of decreasing trends have shown quite similarity
363 to the expansion of urban impervious surface, and *RH* in core cities in all three urban
364 agglomerations generally decreased sharply in succession after 2000, corresponding to
365 the accelerated urban expansion process. Thus, focusing on the cause of urban drying
366 climate after 2000 helps advancing understanding in the effects of urbanization on
367 local and regional climate.

368 *3.3 Enhanced UDI Explained by ET Decline*

369 *ET* is the main source of water vapor in the air, and its changes are closely related
370 to the changes of atmospheric humidity above the ground (Ackerman, 1987; Moriwaki
371 et al., 2013). Through satellite remote sensing data (Fig. 9), it can be found that *ET*
372 in most areas of YRDUA decreased significantly from 2001 to 2017, especially in the
373 central and eastern areas where human activities were most intensive. Northwestern
374 areas of the region first experienced *ET* decline from 2001 to 2009, and then showed
375 significant *ET* rise from 2009 to 2017 compensating for the lost in the first stage to
376 some extent. *ET* in the southern areas kept mounting at various speed for the whole
377 period. In MUA, the northern part first undergone *ET* decline, and then displayed
378 significant *ET* rise after 2011. Southern areas of the region showed a relatively
379 sustained decline of *ET* especially at human gathering areas. In UUA, *ET* in the
380 northwestern areas first decreased overall after 2001, and then increased quite a lot
381 after 2009 except areas under intensive human activities. The eastern parallel ridge
382 valleys of the region first experienced *ET* decline and then *ET* has recovered
383 significantly since 2009.

384 <Fig. 9>

385 Further analysis of the correlations between humidity indicators and *ET* in
386 YRDUA suggests that in the central urban core areas where human activities were

387 intensive, RH , q and e_a all have a significant positive correlation with ET (p
388 <0.1 ; Fig. 10a-c), while VPD and ET have a significant negative correlation (p
389 <0.1 ; Fig. 10d), which indicates that the general ET decline greatly explains the
390 decreasing trend of atmospheric humidity in Nanjing, Shanghai, Hangzhou and their
391 surroundings.

392 <Fig. 10>

393 The correlation analysis between humidity indicators and ET in MUA shows that
394 in the northern and eastern areas, RH , q and e_a all have a significant positive
395 correlation with ET ($p < 0.1$; Fig. 11a-c), while VPD has a significant negative
396 correlation with ET ($p < 0.1$; Fig. 11d). In the central and south-central areas, only
397 q and e_a have a significant positive correlation with ET ($p < 0.1$; Fig. 11b-c), and
398 no significant correlation is found between RH/VPD and ET . Thus, the decreasing
399 trend of humidity in Wuhan, Nanchang and their surroundings can be well explained
400 by ET declines while the small decrease of humidity in Changsha does not correlated
401 well to ET declines. The distribution of the Dongting lake may take a part in the
402 explanation for relatively small changes of atmospheric humidity in Changsha and its
403 surrounding areas. The weak UDI in Wuhan and its surrounding areas may be related
404 to the increase of greening and water areas in recent years.

405 <Fig. 11>

406 Similar correlation analysis performed between humidity indicators and ET in
407 UUA has found that RH has a significant negative correlation with ET ($p < 0.1$) in
408 the eastern parallel ridge valleys and a significant positive correlation with ET (p
409 <0.1 ; Fig. 12a) in the northwestern Chengdu areas. q and e_a both have a significant
410 positive correlation with ET ($p < 0.1$) in the south-central and northwestern areas and
411 a negative correlation with ET ($p < 0.1$; Fig. 12b-c) in the east-central areas. VPD

412 has a significant positive correlation with ET ($p < 0.1$; Fig. 12d) in the eastern
413 parallel ridge valleys and the circumference of the Sichuan Basin. Therefore, the
414 decreasing trend of humidity in northwestern Chengdu Plain and Chongqing central
415 areas can be explained by ET declines to some extent. The atmospheric humidity
416 changes in the eastern areas may be strongly affected by the topography of the eastern
417 parallel ridge valley, which has a great influence on the atmospheric circulation
418 process. Scatterplots of the humidity indicators versus ET were shown in Fig. 13.

419 <Fig. 12>

420 <Fig. 13>

421 Usually air temperature exerts a tremendous influence on atmospheric humidity by
422 altering the ability of air parcels to hold water vapor (Allen and Ingram, 2002;
423 Landsberg and Maisel, 1972; Moriwaki et al., 2013). The station level data (Fig. 3, 4, 5)
424 detected by non-parametric multiple change point analysis in three urban
425 agglomerations shows that there was a common significant change point of TEM
426 with $p < 0.05$ at around 1997 in all urban and rural stations except Nanbu in UUA,
427 which indicates that TEM displayed obvious rise before 2000 and then reached a
428 relatively stable state no matter in urban or rural areas, corresponding to the backdrop
429 of global warming (Liepert et al., 2004; Wild et al., 2004). Thus, the small fluctuations
430 of TEM after 2000 may not be able to explain neither the humidity decline at the
431 same period nor the urban-rural differences in humidity trends. Thus, the enhanced
432 UDI may not be explained by changes of air temperature. A further correlation analysis
433 confirmed that no significant correlation between RH and TEM was found in
434 urban core areas (Fig. 14).

435 <Fig. 14>

436 3.4 ET Reduction as a Result of LAI Decrease under Urban Expansion

437 Through further analysis of the changing process of LAI in the YREB (Fig. 15),
438 it can be seen that LAI decreased in almost all areas in YRDUA except the southern

439 part from 2001 to 2017. The decrease was more obvious from 2001 to 2009, and then
440 the decreasing rate visibly slowed down from 2009 to 2017. Changes of *LAI* in
441 MUA were more obvious in the northern, southwestern and southeastern areas where
442 human activities were intensive, with different speed of decline. *LAI* of almost all
443 areas in UUA showed decline from 2001 to 2017, except the circumference of the
444 Sichuan Basin. Overall, the *LAI* decrease in the YRDUA region was the most
445 significant, and the UUA region had the smallest decrease, which coincided with the
446 different levels of rapid urban expansion process of the three urban agglomerations
447 after 2000. What's more, almost all areas of the three urban agglomerations had a
448 significant positive correlation between *ET* and *LAI* ($p < 0.1$; Fig. 16). This
449 strongly suggests that LUCC has greatly changed the vegetation coverage, thereby
450 affecting the corresponding evapotranspiration process and the water vapor content in
451 the air, i.e., the atmospheric humidity.

452 <Fig. 15>

453 <Fig. 16>

454 **4 Conclusions**

455 In this study, a linear regression method was employed to detect the trends of
456 humidity indicators in three urban agglomerations with different levels of urbanization
457 in the YREB at the pixel level during 1965-2017, and the significance of the trend was
458 tested by the nonparametric Mann-Kendall test. We found different degrees of urban
459 dry island (UDI) effects in the three urban agglomerations, which was featured by
460 humidity decrease and vapor pressure deficit increase of varying severity. Among all,
461 the Yangtze River Delta urban agglomeration (YRDUA) with the fastest urbanization
462 process and the largest percentage of urban impervious surface (0.641% in 1978 and
463 11.768% in 2017) had the most obvious UDI effect, with the maximum changing
464 speeds of relative humidity and vapor pressure deficit reaching -2.396% per decade
465 and 0.720 hPa per decade. The midstream urban agglomeration (MUA) and the
466 upstream urban agglomeration (UUA) with relatively few but close urban impervious

467 surface (2.413% and 1.956% in 2017) had weaker UDI effects than YRDUA, with the
468 maximum changing rates of -1.977% per decade and -1.982% per decade of relative
469 humidity, and 0.588 hPa per decade and 0.582 hPa per decade of vapor pressure deficit
470 for MUA and UUA.

471 Further a multiple change point analysis performed at the core cities and their
472 surrounding rural stations suggested that there was a general change point of relative
473 humidity at about 2000 in all three urban agglomerations, corresponding to the
474 accelerated urban expansion process after 2000. The correlation analyses were
475 performed between atmospheric humidity indicators and *ET*, between atmospheric
476 humidity indicators and air temperature, and between *ET* and *LAI* to explore the
477 mechanism of possible LUCC effects on local and regional atmospheric humidity. We
478 found that the urban expansion with rapidly growing impervious surface at the expense
479 of vegetation cover had a strong influence on regional atmospheric humidity.
480 Specifically, atmospheric humidity decreased due to *ET* decline as a result of *LAI*
481 decrease, indicating that urban expansion could affect regional climate through
482 modifying the *ET* part in the ecohydrological process.

483 What's more, it was also found that core cities tended to form dry land clusters
484 instead of an isolated dry island due to the urban expansion and connectivity. We
485 speculate that the UDI effect will not appear until urbanization development reaches to
486 a certain scale when a large quantity of vegetation cover is replaced by impervious
487 surface, and the urbanization-induced LUCC may exert a larger influence on UDI than
488 on UHI. Thus, the UDI effect may be more prominent than the UHI effect in the later
489 period of accelerated urban expansion. Considering that future cities will continue to
490 develop into urban agglomerations, the standing out impacts of urbanization on local
491 and regional climate, especially on atmospheric humidity, should attract wider
492 attention so as to mitigate climate change and maintain sustainable development.

493 **Declarations**

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499 **Conflicts of interest:** None.

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671

672 **Tables**

673 **Table 1** Basic information of the study area

	YRDUA	MUA	UUA
Coverage	26 cities	31 cities	16 cities
Core cities	Shanghai, Nanjing, Hangzhou	Wuhan, Nanchang, Changsha	Chengdu, Chongqing
Land area (km ²)	211,700	317,000	185,000
Population (million)	150	121	91

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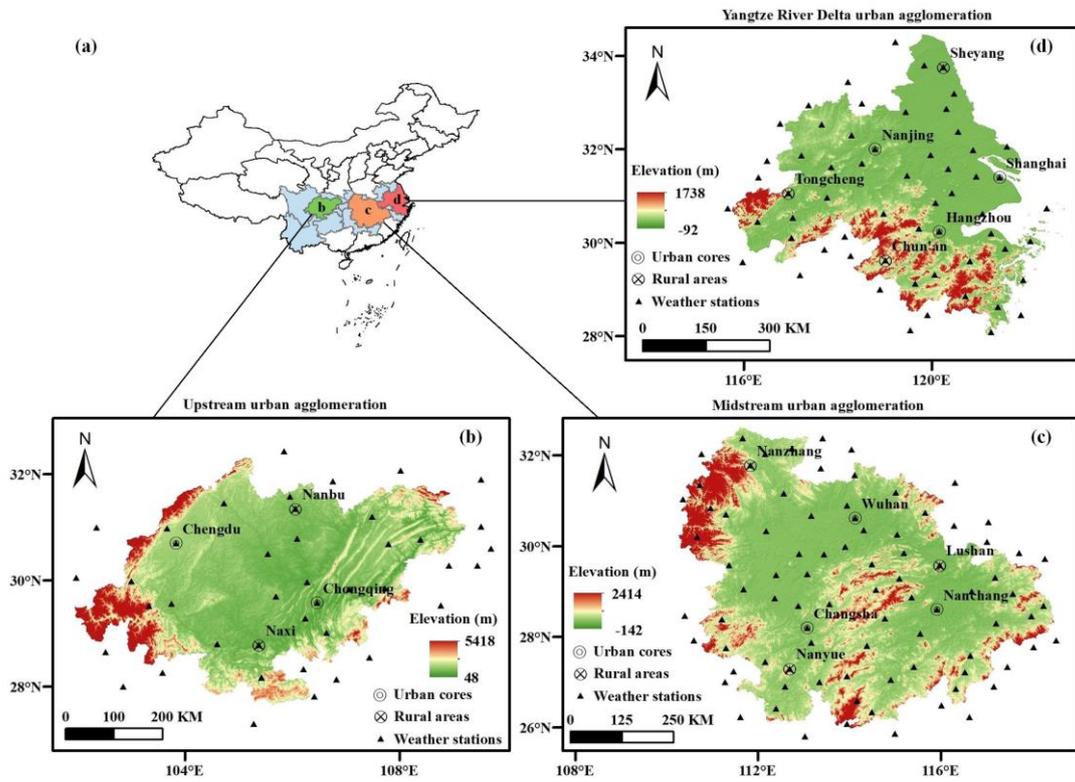
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676 **Table 2** Linear trends of humidity indicators in core cities and the surrounding areas in the YREB
 677 during 1965-2017 (the bold numbers indicating significant trends with $p < 0.1$; RH: relative
 678 humidity, q : specific humidity, e_a : actual vapor pressure, VPD: vapor pressure deficit)

	RH (% per decade)	q (g/kg per decade)	e_a (hPa per decade)	VPD (hPa per decade)
Nanjing	-1.3592	-0.0164	-0.0329	0.4073
Shanghai	-2.1950	-0.0358	-0.0575	0.6960
Hangzhou	-1.8192	-0.0158	-0.0338	0.6201
Tongcheng	0.0362	0.1167	0.1657	0.0386
Sheyang	-0.3989	0.1014	0.1640	0.1538
Chun'an	-0.3326	0.0773	0.1207	0.1222
Wuhan	-0.8042	0.0661	0.1056	0.3451
Nanchang	-1.1495	0.0046	0.0090	0.4051
Changsha	-0.4862	0.0939	0.1362	0.2116
Nanzhang	-0.2748	0.1011	0.1440	0.0558
Lushan	-0.2152	0.1404	0.1971	0.0618
Nanyue	0.0313	0.1402	0.1950	0.0163
Chengdu	-1.4449	-0.0370	-0.0581	0.3827
Chongqing	-0.6609	0.0036	0.0074	0.2962
Nanbu	-0.2393	0.1110	0.1504	0.1658
Naxi	-0.1013	0.1186	0.1770	0.0953

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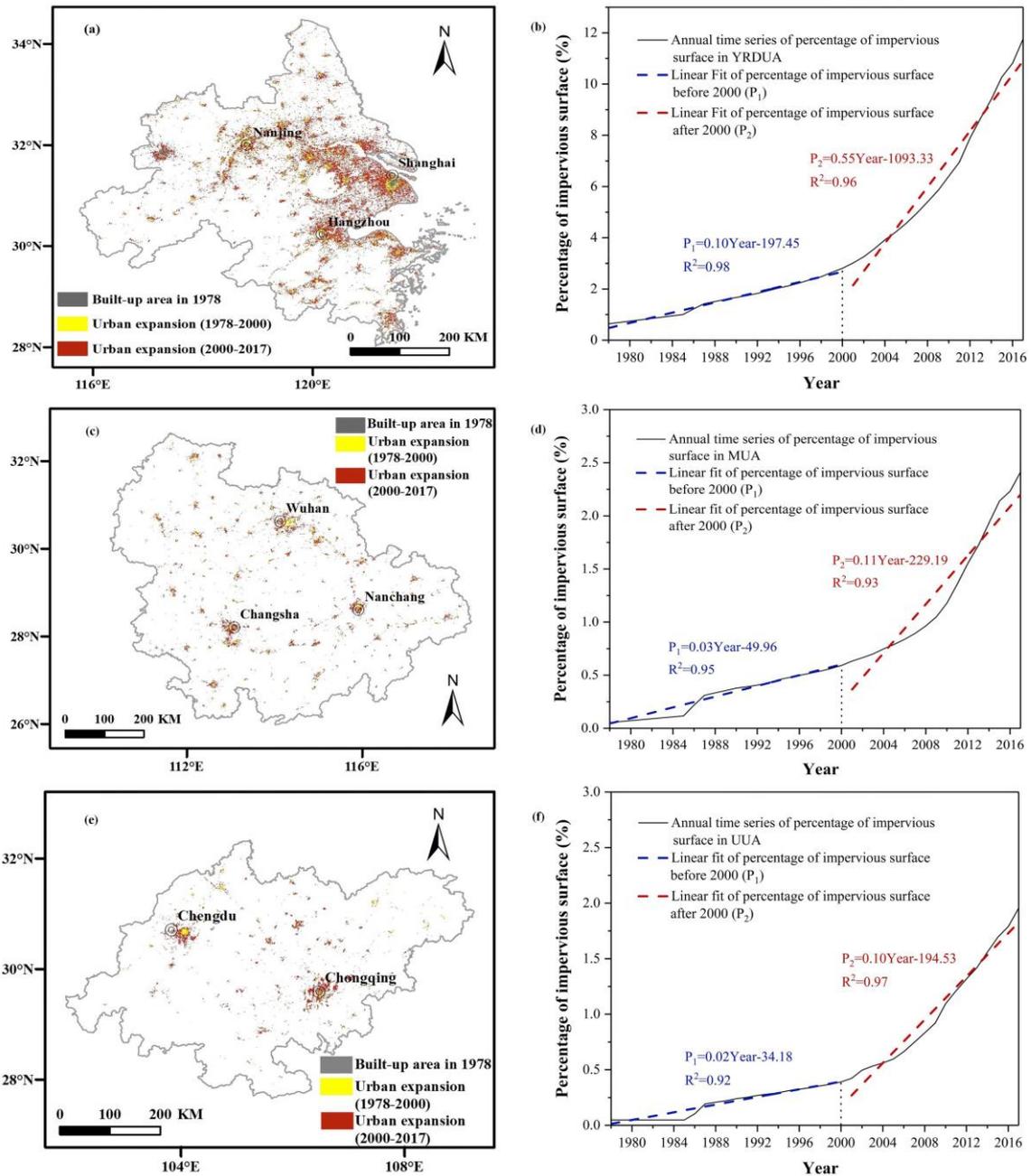
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682
 683 **Fig. 1** Location and distribution of the weather stations, urban cores and rural areas of the study
 684 area: (a) the Yangtze River Economic Belt (YREB), (b) the upstream urban agglomeration (UUA),
 685 (c) the midstream urban agglomeration (MUA) and (d) the Yangtze River Delta urban
 686 agglomeration (YRDUA)

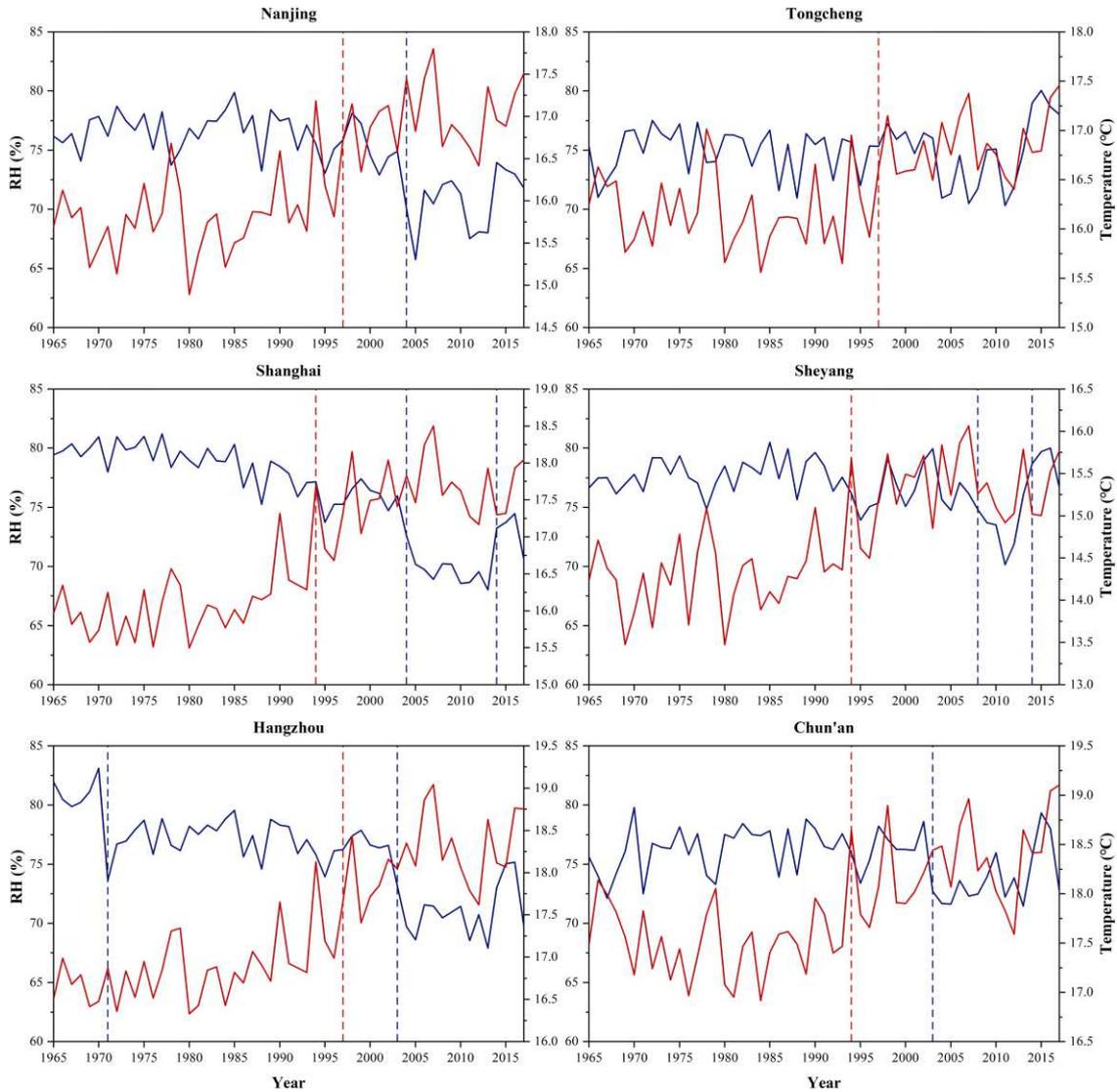
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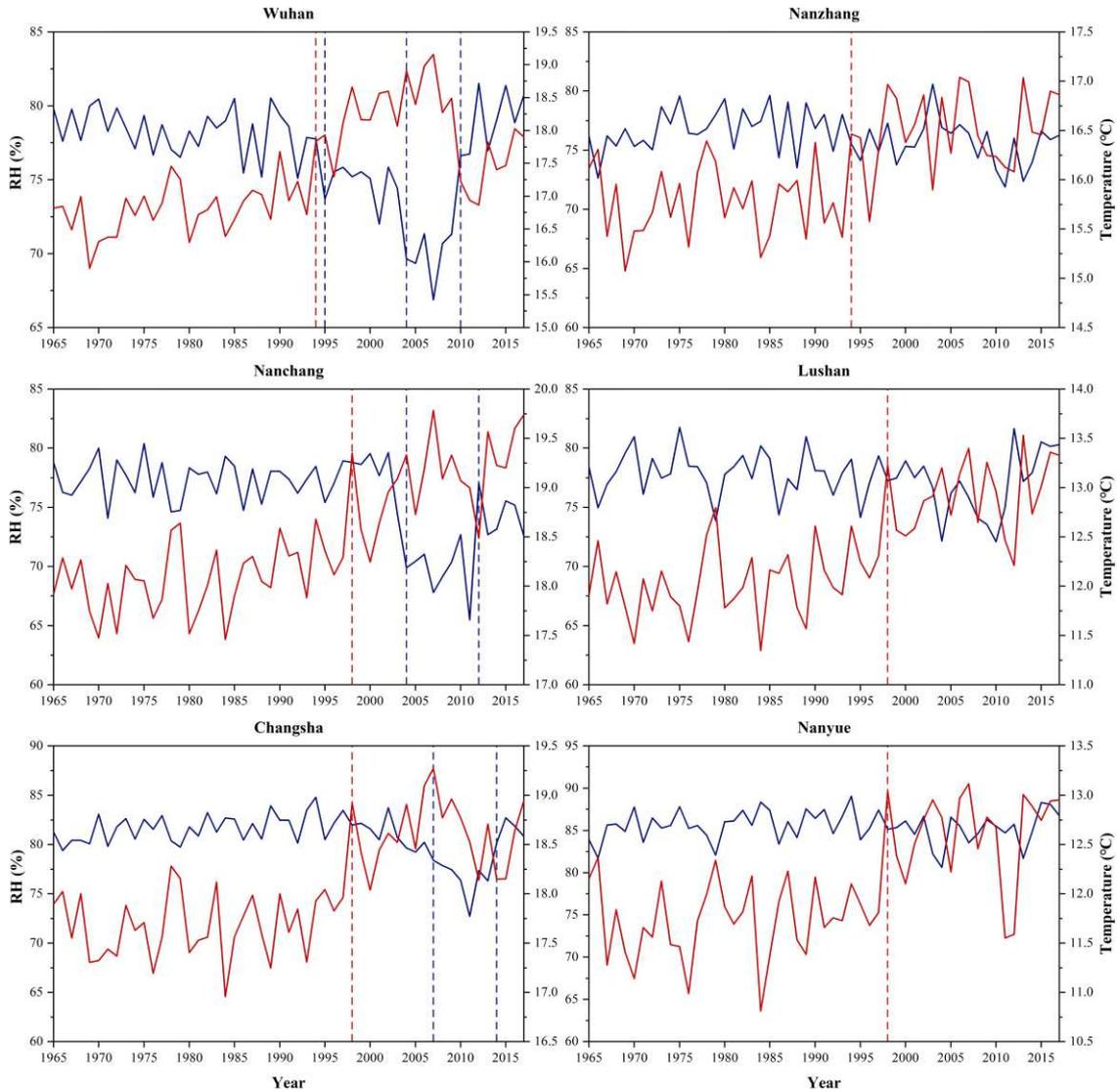


689
 690 **Fig. 2** Urban expansion processes of (a) the YRDUA, (c) the MUA and (e) the UUA from 1978 to
 691 2017, and annual time series and linear fit of percentage of urban impervious surface of (b)
 692 YRDUA, (d) MUA and (f) UUA

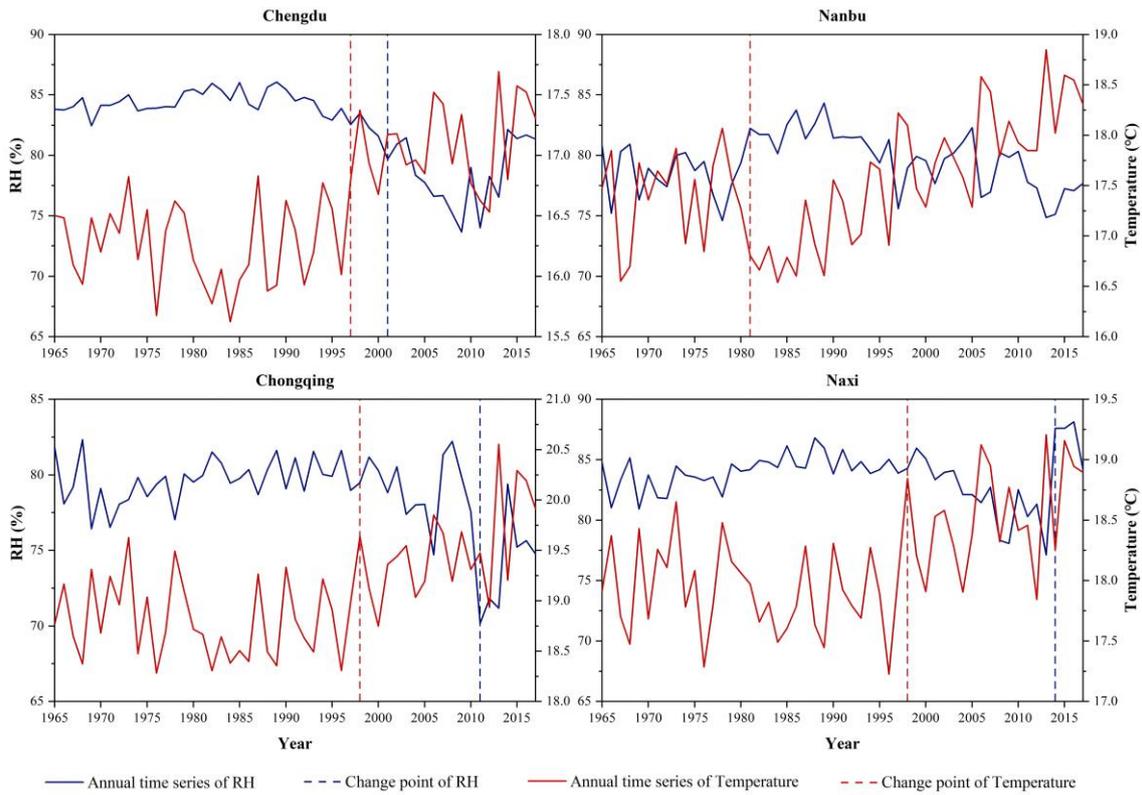
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694 — Annual time series of RH - - - Change point of RH — Annual time series of Temperature - - - Change point of Temperature
 695 **Fig. 3** Observed annual mean relative humidity (blue solid lines) and air temperature (red solid
 696 lines) of core cities (double circles in Fig. 1d, left in Fig. 3) and rural areas (cross circles in Fig. 1d,
 697 right in Fig. 3; 1965-2017) in the YRDUA (blue and red dashed lines indicating change points of
 698 relative humidity and air temperature, respectively)
 699



700 ——— Annual time series of RH - - - Change point of RH ——— Annual time series of Temperature - - - Change point of Temperature
 701 **Fig. 4** Observed annual mean relative humidity (blue solid lines) and air temperature (red solid
 702 lines) of core cities (double circles in Fig. 1c, left in Fig. 4) and rural areas (cross circles in Fig. 1c,
 703 right in Fig. 4; 1965-2017) in the MUA (blue and red dashed lines indicate change points of relative
 704 humidity and air temperature, respectively)
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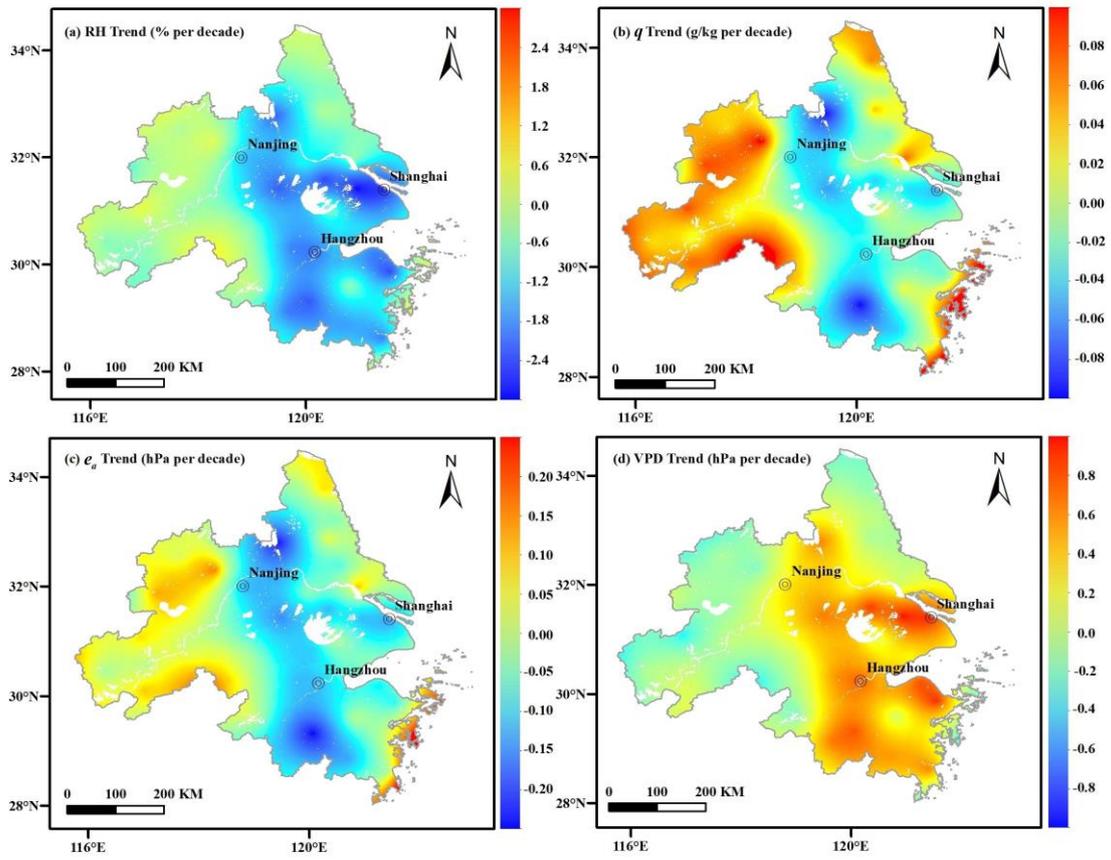
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Fig. 5 Observed annual mean relative humidity (blue solid lines) and air temperature (red solid lines) of core cities (double circles in Fig. 1b, left in Fig. 5) and rural areas (cross circles in Fig. 1b, right in Fig. 5; 1965-2017) in the UUA (blue and red dashed lines indicate change points of relative humidity and air temperature, respectively)

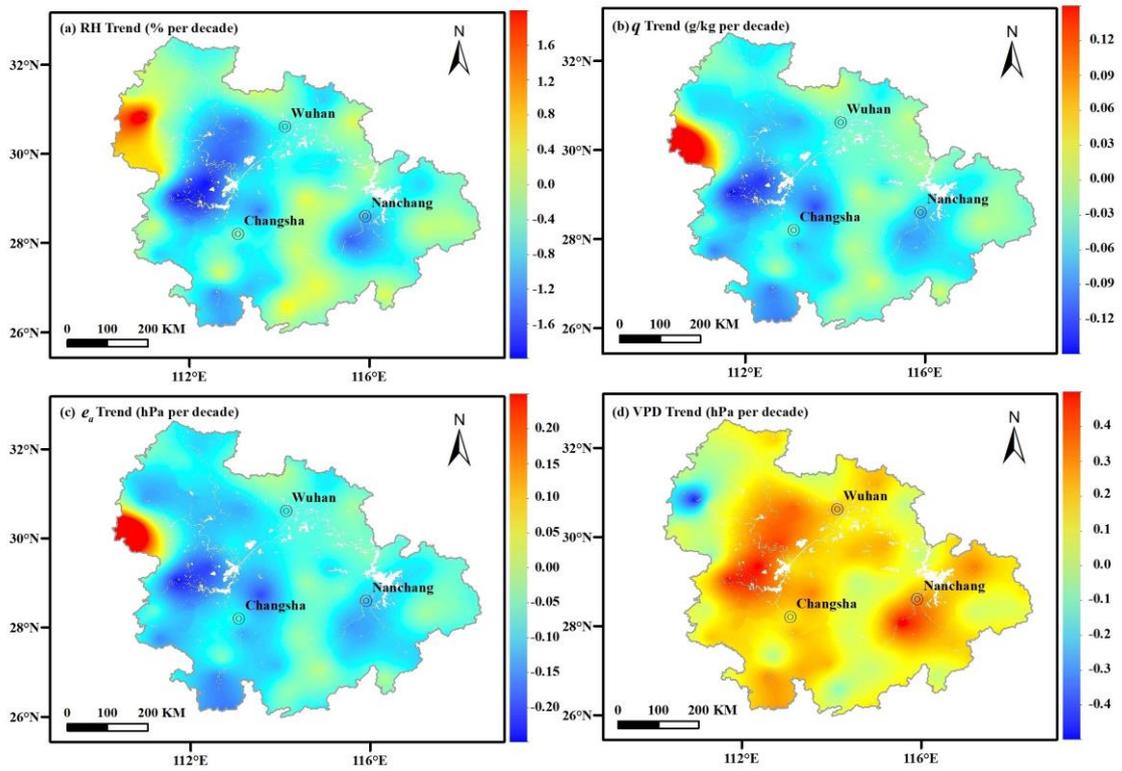


712

713 **Fig. 6** Linear trends of annual mean (a) relative humidity (RH), (b) specific humidity (q), (c)

714 actual vapor pressure (e_a) and (d) vapor pressure deficit (VPD) across the YRDUA (1965-2017)

715

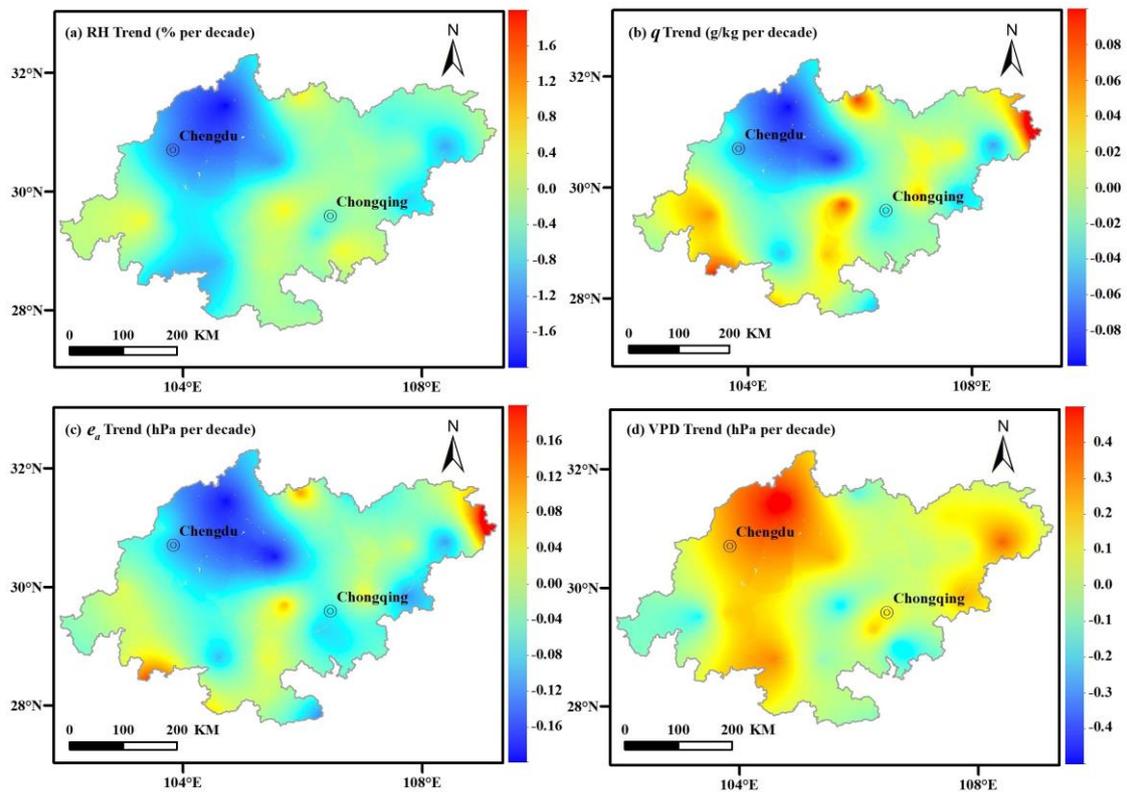


716

717 **Fig. 7** Linear trends of annual mean (a) relative humidity (RH), (b) specific humidity (q), (c)

718 actual vapor pressure (e_a) and (d) vapor pressure deficit (VPD) across the MUA (1965-2017)

719

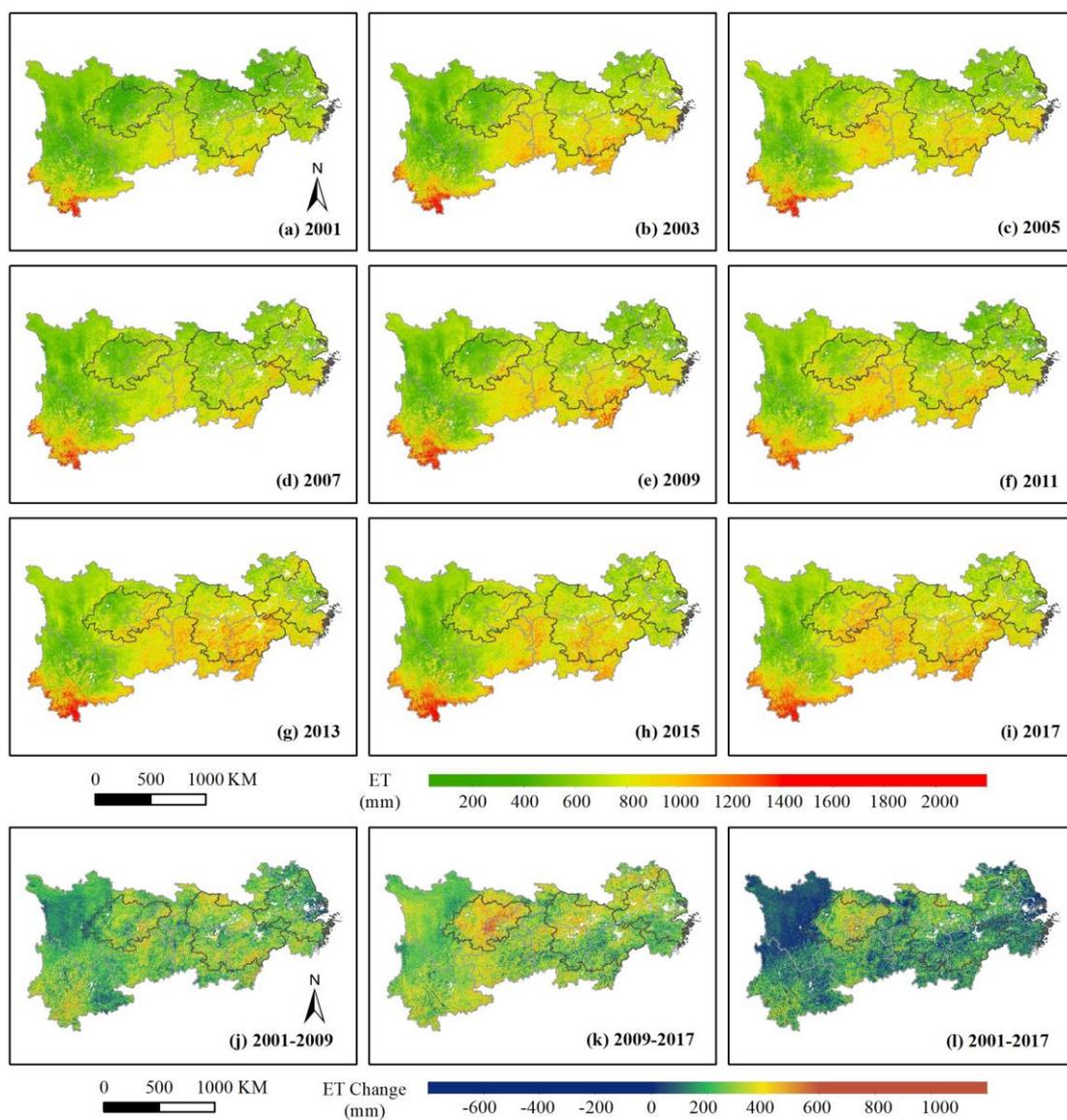


720

721 **Fig. 8** Linear trends of annual mean (a) relative humidity (RH), (b) specific humidity (q), (c)

722 actual vapor pressure (e_a) and (d) vapor pressure deficit (VPD) across the UUA (1965-2017)

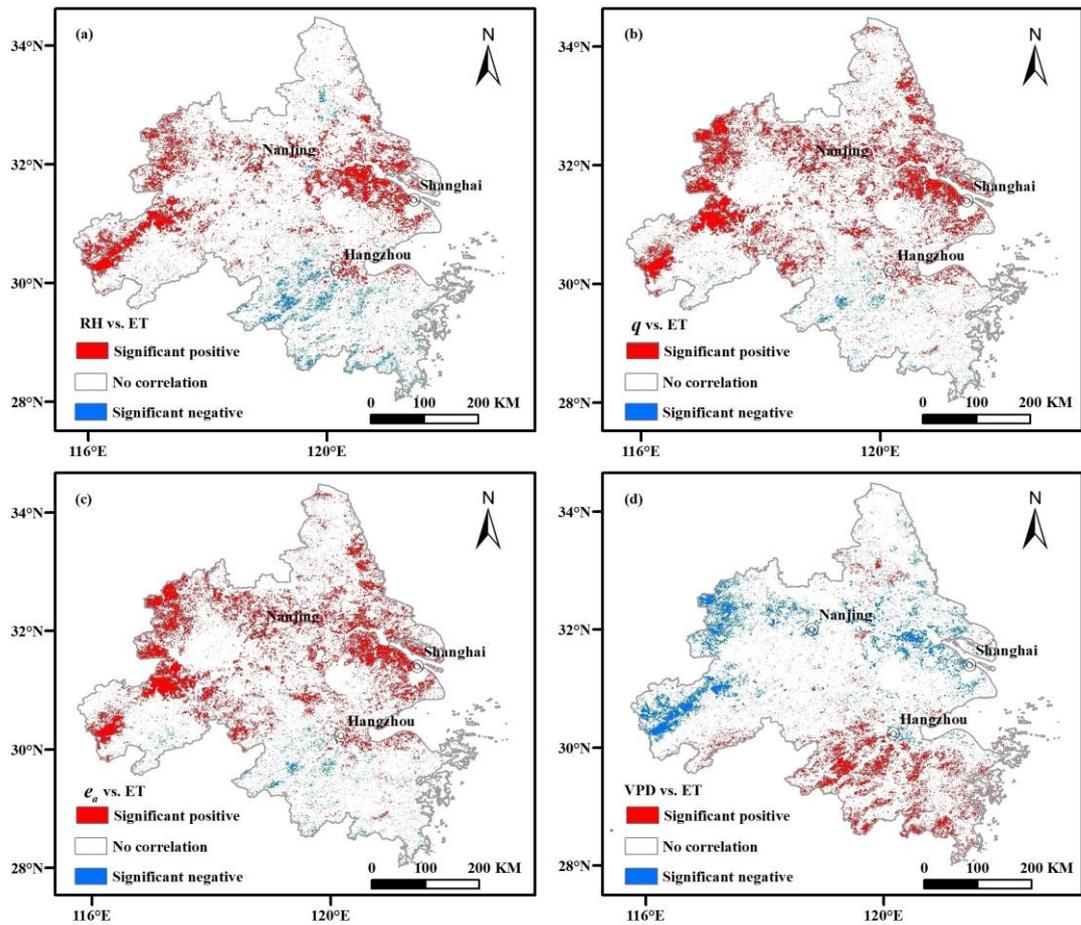
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725 **Fig. 9** Annual *ET* (a-i) and its changes (j-l) of the YREB from 2001 to 2017 (gray contours from
 726 the west to the east representing the UUA, the MUA and the YRDUA, respectively)

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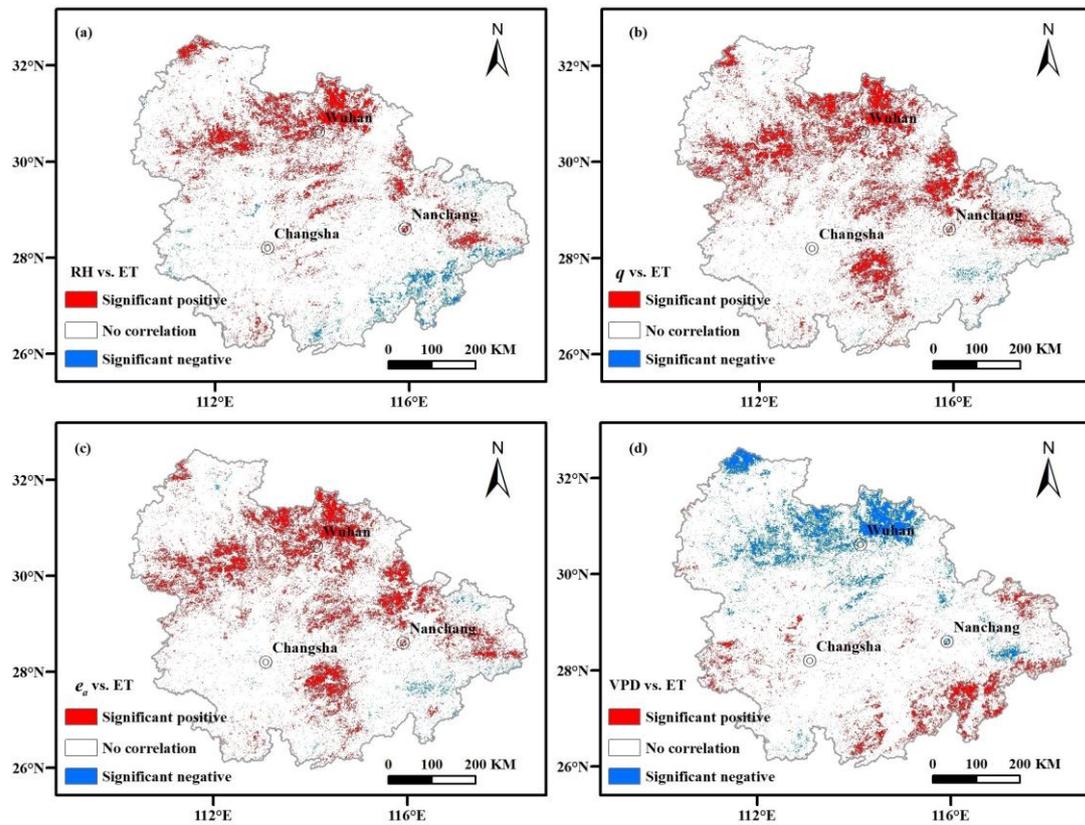
729 **Fig. 10** Correlations of (a) RH versus ET , (b) q versus ET , (c) e_a versus ET , and (d)

730 VPD versus ET in the YRDUA (red and blue areas representing significant positive and

731 negative correlation with $p < 0.1$, respectively, and the blank space representing no significant

732 correlation; 2001-2017)

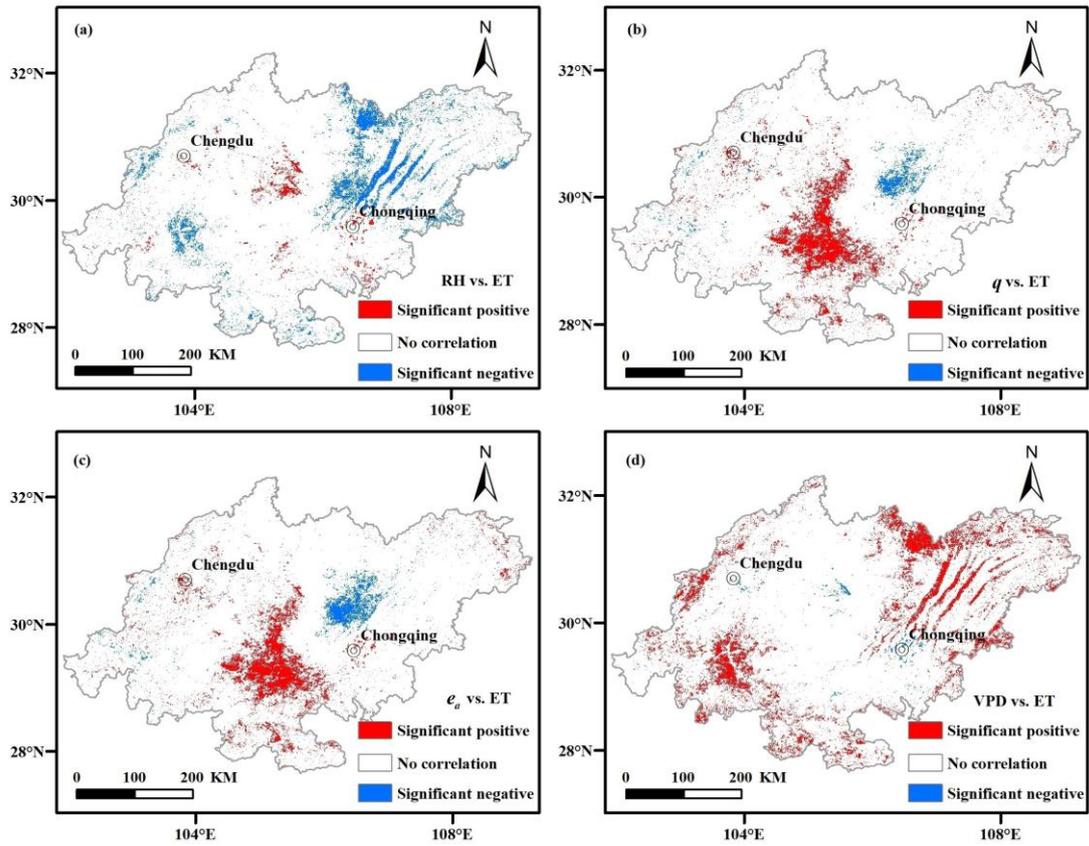
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734

735 **Fig. 11** Correlations of (a) RH versus ET , (b) q versus ET , (c) e_a versus ET , and (d)
 736 VPD versus ET in the MUA (red and blue areas representing significant positive and negative
 737 correlation with $p < 0.1$, respectively, and the blank space representing no significant correlation;
 738 2001-2017)

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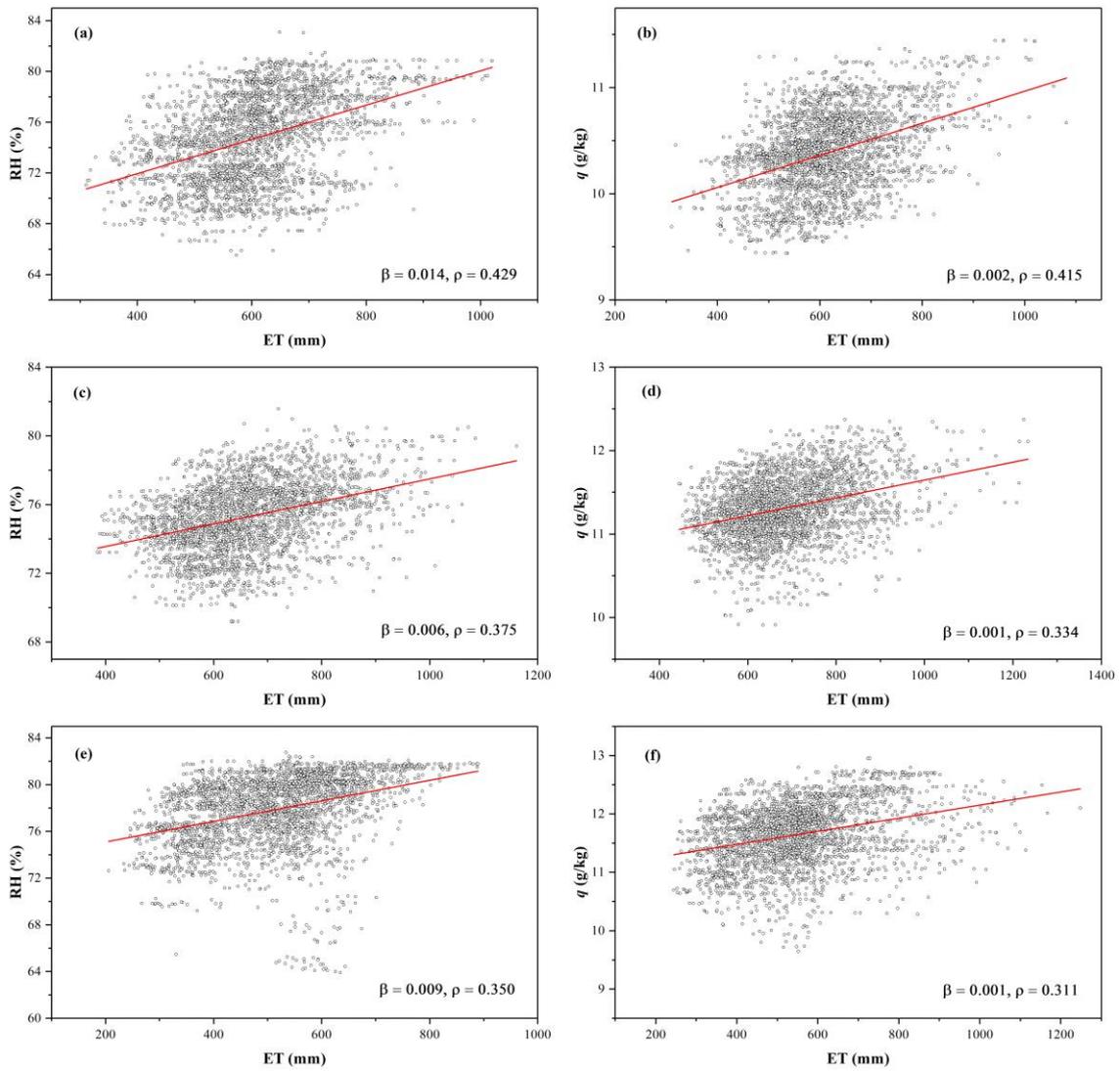
741 **Fig. 12** Correlations of (a) RH versus ET , (b) q versus ET , (c) e_a versus ET , and (d)

742 VPD versus ET in the UUA (red and blue areas representing significant positive and negative

743 correlation with $p < 0.1$, respectively, and the blank space representing no significant correlation;

744 2001-2017)

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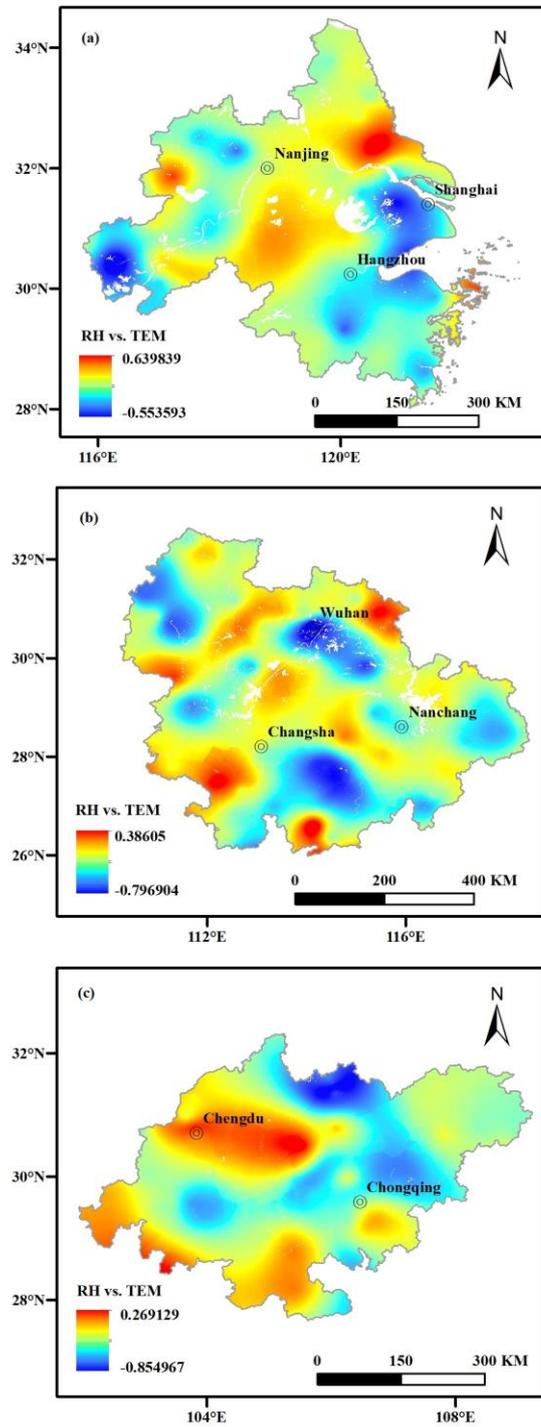
747 **Fig. 13** Scatterplots of the humidity indicators versus ET of the significant positive correlation

748 areas in (a-b) the YRDU, (c-d) the MUA, and (e-f) the UUA (β denoting the slope of the fitted

749 line; ρ is the Pearson's correlation coefficient between the humidity indicator and ET , and all

750 correlation coefficients are significant with $p < 0.05$)

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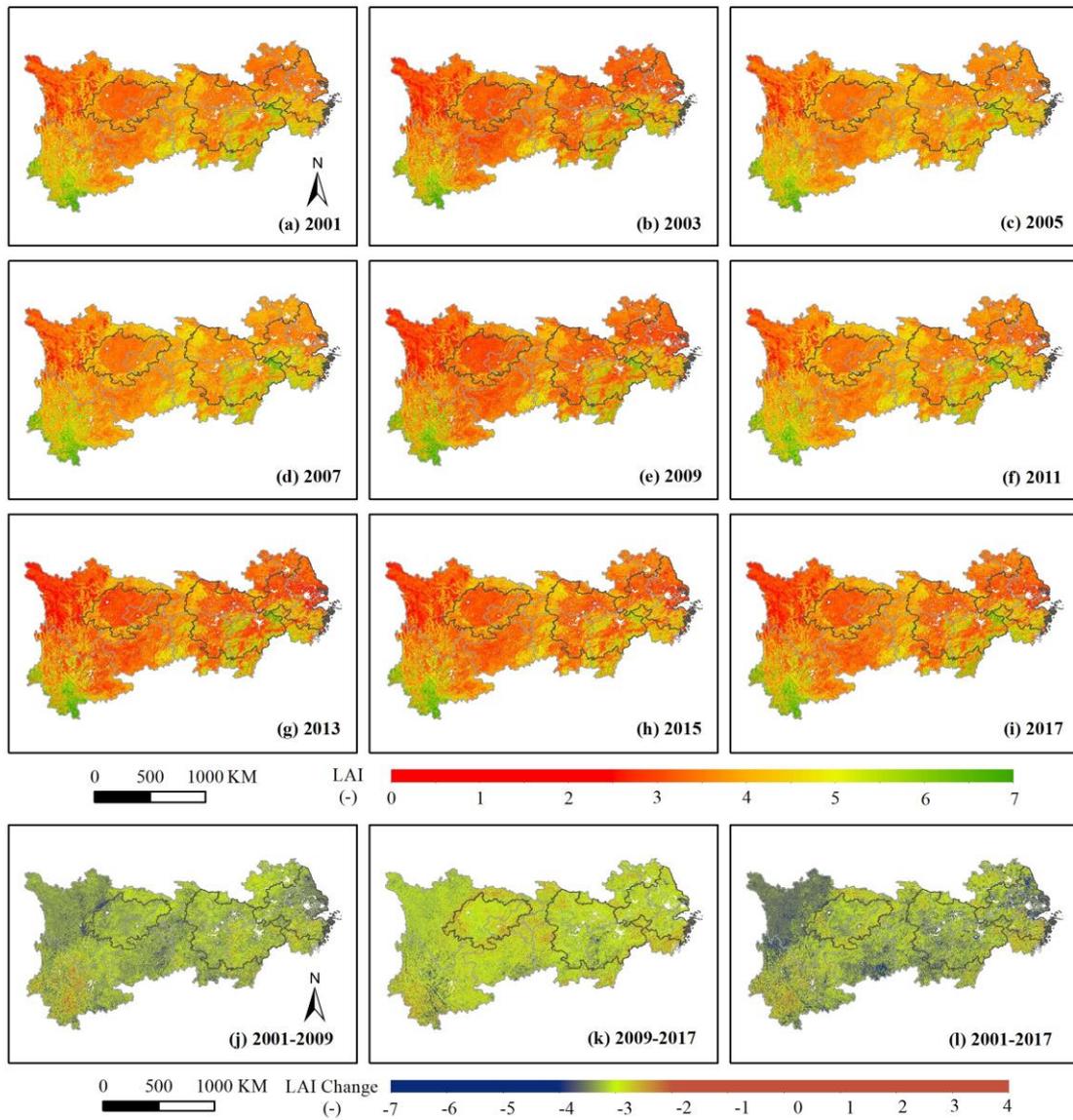


752

753 **Fig. 14** Correlations of *RH* versus air temperature (*TEM*) in (a) the YRDUA, (b) the MUA and

754 (c) the UUA (2001-2017)

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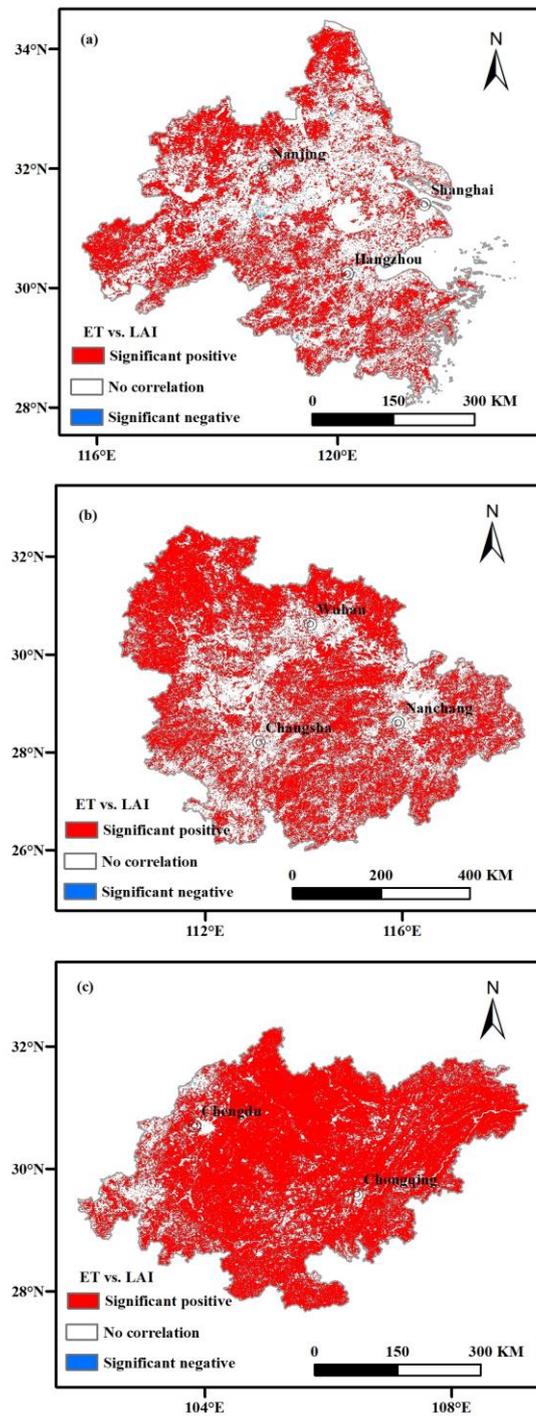


756

757 **Fig. 15** Annual mean *LAI* (a-i) and its changes (j-l) in the YREB from 2001 to 2017 (gray

758 contours from the west to the east representing the UUA, the MUA and the YRDUA, respectively)

759



760

761 **Fig. 16** Correlations of *ET* versus *LAI* in (a) the YRDUA, (b) the MUA and (c) the UUA (red
 762 and blue areas representing significant positive and negative correlation with $p < 0.1$, respectively,
 763 and the blank space representing no significant correlation; 2001-2017)