

Manuscript Number: STOTEN-D-19-14613R2

Title: Gravimetry-based water storage shifting over the China-India border area controlled by regional climate variability

Article Type: Research Paper

Keywords: Water storage shifting; Gravity Recovery and Climate Experiment; climate variability; China-India border area

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Abstract: The regional water storage shifting causes nonstationary spatial distribution of droughts and flooding, leading to water management challenges, environmental degradation and economic losses. The regional water storage shifting is becoming evident due to the increasing climate variability. However, the previous studies for climate drivers behind the water storage shifting are not rigorously quantified. In this study, the terrestrial water storage (TWS) spatial shifting pattern during 2002-2017 over the China-India border area (CIBA) is developed using the Gravity Recovery and Climate Experiment (GRACE), suggesting that the northwestern India were wetting while western China was drying. Similar drying and wetting patterns were also found in the precipitation, snow depth, Palmer Drought Severity Index (PDSI) and potential evaporation data. Based on our newly proposed Indian monsoon (IM) and western North Pacific monsoon (WNPM) variation indices, the water shifting pattern over the CIBA was found to be affected by the weakening of the variation of IM and WNPM through modulating the regional atmospheric circulation. The weakening of IM and WNPM variations has shown to be attributed to the decreasing temperature gradient between the CIBA and the Indian Ocean, and possibly related to increasing regional temperatures associated with the increasing global temperature. As the global warming intensifies, it is expected that the regional TWS shifting pattern over the CIBA will be further exaggerated, stressing the need of advancing water resources management for local communities in the region.

Response to Reviewers: Dear Dr Ouyang,

Thank you for being the editor of this manuscript. We also would like to thank the reviewers' comments and suggestions.

Please find the revised version of "Gravimetry-based water storage shifting over the China-India border area controlled by regional climate variability" with one author's new affiliation. We also provide new supporting materials for this manuscript.

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Reviewer #2: Authors have addressed the review comments satisfactorily, and improved the presentation in the manuscript.

For the benefit of readers, Authors should include the supporting codes used in the study as supporting material (or provide it in links/open source platform)

Response to Reviewer 2 comment: Thank you for the comments. Following the suggestion, we have provided new supporting documents including a data resource list, codes and a data file of the new indices mentioned in the manuscript. The details are described in the Readme file.

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19 **Highlights:**

- 20 • Terrestrial water storage showed a clear shifting pattern
- 21 • Pattern showed wetting in western China and drying in northwestern India.
- 22 • The shifting patterns were mainly due to the weakening of the monsoon
- 23 variations.
- 24 • Weakening monsoon were related to decreasing regional temperature gradients.

25 **Abstract**

26 The regional water storage shifting causes nonstationary spatial distribution of droughts
27 and flooding, leading to water management challenges, environmental degradation and
28 economic losses. The regional water storage shifting is becoming evident due to the
29 increasing climate variability. However, the previous studies for climate drivers behind
30 the water storage shifting are not rigorously quantified. In this study, the terrestrial
31 water storage (TWS) spatial shifting pattern during 2002-2017 over the China-India
32 border area (CIBA) is developed using the Gravity Recovery and Climate Experiment
33 (GRACE), suggesting that the northwestern India were wetting while western China
34 was drying. Similar drying and wetting patterns were also found in the precipitation,
35 snow depth, Palmer Drought Severity Index (PDSI) and potential evaporation data.
36 Based on our newly proposed Indian monsoon (IM) and western North Pacific
37 monsoon (WNPM) variation indices, the water shifting pattern over the CIBA was
38 found to be affected by the weakening of the variation of IM and WNPM through
39 modulating the regional atmospheric circulation. The weakening of IM and WNPM

40 variations has shown to be attributed to the decreasing temperature gradient between
41 the CIBA and the Indian Ocean, and possibly related to increasing regional
42 temperatures associated with the increasing global temperature. As the global warming
43 intensifies, it is expected that the regional TWS shifting pattern over the CIBA will be
44 further exaggerated, stressing the need of advancing water resources management for
45 local communities in the region.

46 **Keywords**

47 Water storage shifting; Gravity Recovery and Climate Experiment; climate variability;
48 China-India border area

49 **1 Introduction**

50 Terrestrial water storage (TWS), including canopy water, glaciers, snow,
51 surface water in rivers, lakes, wetlands and reservoirs, and underground water,
52 determines global and regional hydrological resilience (Alsdorf et al., 2007). It plays a
53 major role in the exchange of water with the atmosphere and oceans, and affects
54 climate variability (Kim et al., 2009). Therefore, the TWS monitoring as well as the
55 underlying drivers for its spatiotemporal dynamics are crucial for understanding the
56 climatic-hydrological system (Humphrey et al., 2016). With the launch of the Gravity
57 Recovery and Climate Experiment (GRACE) in March 2002, it provides a novel and
58 reliable tool for TWS monitoring (e.g., Long et al., 2015; Long et al., 2017; Reager
59 and Famiglietti, 2009b; Scanlon et al., 2019; Schmidt et al., 2006b; Sinha et al., 2016;
60 Syed et al., 2008; Tapley et al., 2004).

61 In recent years, the GRACE data has been widely used to assess the TWS
62 variability (e.g., Güntner et al., 2007; Long et al., 2015; Schmidt et al., 2006a), to
63 monitor droughts (e.g., Houborg et al., 2012; Thomas et al., 2014; Yi and Wen, 2016;
64 Zhao et al., 2017) and flooding (e.g., Chen et al., 2010; Reager and Famiglietti, 2009a;
65 Reager et al., 2014); it is also used to evaluate groundwater depletion (e.g., Long et al.,
66 2016; Rodell et al., 2009; Thomas and Famiglietti, 2019), and to estimate ice sheet or
67 glacier loss (e.g., Chen et al., 2009; Farinotti et al., 2015; Shepherd et al., 2018).
68 These studies have demonstrated the capability of GRACE to observe regional
69 hydrological variability and global climate abnormalities, which are used for
70 investigated water cycles linked with global and regional climates. For investigating
71 the GRACE long-term trend variability, Rodell et al. (2018) quantified the global
72 TWS trends during 2002-2016 and provided their corresponding causes. They found a
73 general wetting pattern at high- and low-latitudes and a drying pattern at mid-latitudes,
74 and these patterns are mainly due to the regular natural variability, groundwater
75 depletion, and climate change. Meanwhile, Scanlon et al. (2018) found the TWS in
76 some mid-latitude basins were decreasing, including Arkansas, Indus, Ganges,
77 Brahmaputra, Hai River, Euphrates. On the other hand, high- and low-latitude regions
78 showed an increasing TWS trend including Missouri, Amazon, Okavango, and
79 Murray basin.

80 The increasing water loss at mid-latitudes exerts great pressure on the water
81 supply in mid-latitude countries, in particular populous China and India. The
82 China-India border area (CIBA, Figure 1), covering the Qinghai-Tibet Plateau (QTP),

83 and Indus-Ganges-Brahmaputra basin (IGBB), is shared by multiple nations,
84 including China, India, Nepal, Bhutan, Bangladesh, and Pakistan. The Tibetan Plateau,
85 known as the ‘third pole’ of the Earth (Yao et al., 2012), affects regional thermal
86 gradients which modulate local circulations (Duan et al., 2018; Wu et al., 2014; Zhao
87 and Chen, 2001). Therefore, exploring how local climate mechanisms affect the TWS
88 variability over the CIBA can provide information to decision makers for managing
89 water resources shared among multiple populous nations. Over the IGBB, there have
90 been several studies focusing on the water storage variations over the IGBB (e.g.,
91 Khandu et al., 2016; Scanlon et al., 2018) and QTP regions (e.g., Song et al., 2015;
92 Xiang et al., 2016; Zhang et al., 2017). Related to the glacial processes, sharp water
93 mass losses were observed in the southeast QTP between 2003 and 2011 (Song et al.,
94 2015). Moreover, the lake volume in QTP region increased from 1970s to 2015
95 (Zhang et al., 2017). Over the IGBB, the TWS declined rapidly due to decreasing
96 precipitation during 2002-2014 (Khandu et al., 2016) and increasing irrigation
97 (Scanlon et al., 2018). Overall, previous studies clearly showed the separate trend
98 variations of TWS in QTP and IGBB. Although they attempted to explain the TWS
99 variations using meteorological forcing (e.g. precipitation and temperature) and
100 human influences (e.g. irrigation), the TWS variations over the IGBB can be
101 associated with the water conditions over the QTP, since the headwaters of the Indus,
102 Ganges and Brahmaputra rivers originate in the QTP region (Kuehl et al., 2011).
103 Therefore, there is a need to investigate the TWS dynamic in the QTP and the IGBB
104 as an integral system rather than individual separate components. Furthermore, the

105 TWS variations are not only directly controlled by the local precipitation and
106 temperature, but also indirectly affected by regional atmospheric circulations and
107 temperature gradients between land and ocean.

108 Over the IGBB, the spatiotemporal dynamic of the hydrological regime is
109 mainly under the control of the Indian monsoon (IM) (Khandu et al., 2017). Over the
110 IGBB from July to September, the IM contributes to around 60-90% of the annual
111 precipitation (Khandu et al., 2016). Due to the complex climate types, (Figure 1b), the
112 IGBB has unevenly distributed precipitation over the sub-basins. In the Ganges basin,
113 the northwest region is dryer than the coast area; in the Brahmaputra basin, there is
114 heavy precipitation because of the rain shadow effect (Mirza et al., 1998). The upper
115 Indus basin receives more precipitation than the lower basin, especially in the
116 mountain region (Archer et al., 2010). Furthermore, the formation and variation of the
117 IM are closely related to the QTP heating (Feng and Hu, 2005; Molnar et al., 1993;
118 Sato and Kimura, 2007), and the IM affects precipitation patterns and river
119 distributions over the QTP (Yao et al., 2009). Therefore, the IM plays an crucial role
120 in the water dynamics over the whole CIBA.

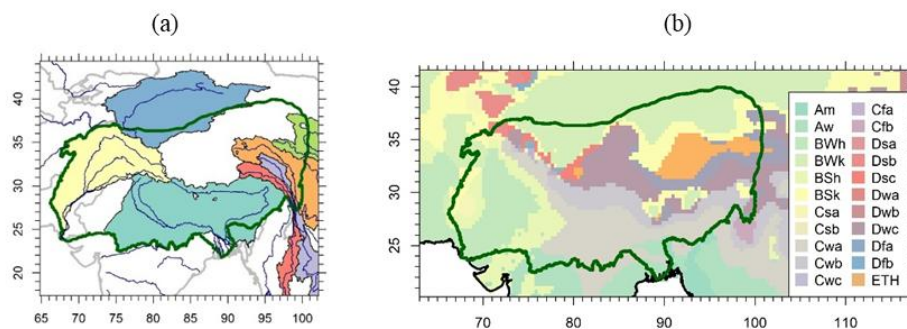
121 Apart from the influence of IM, the regional temperature gradient could be an
122 indirect contributor to the hydrological variability over the IGBB region. For instance,
123 Roxy et al. (2015) found that the decreasing land-sea thermal gradient weakens the
124 summer monsoon circulation and leads to the rainfall variations in India, due to rapid
125 Indian Ocean warming. Over the past decades, the regional temperature increase

126 caused wetter conditions in central and northern QTP (Yang et al., 2014). Moreover,
127 changing hydroclimatic extreme events over the QTP and IGBB region are suggested
128 to be related to shifting atmospheric and hydrological patterns due to increasing
129 global average temperatures (Wijngaard et al., 2017). In recent years, more frequent
130 droughts occurred in central India (Mallya et al., 2016; Rajeevan and Bhate, 2009),
131 Nepal (Baidya et al., 2008), and Bangladesh (Shahid, 2011), while the extreme
132 precipitation events were increased over the most parts of the India (Roxy et al., 2017;
133 Sen Roy and Balling, 2004). In the central QTP, grasslands were affected by flooding
134 due to the expansion of the surrounding lakes since the early 2000s (Zhu et al., 2010).

135 Over the CIBA, the changes of precipitation driven by IM variability affect the
136 TWS dynamic (e.g., Khandu et al., 2016; Papa et al., 2010; 2015). The relationships
137 between the IM and the TWS over the CIBA were only discussed qualitatively in
138 almost all previous studies, but few studies have quantified these relationships and
139 analyzed their mechanisms associated with regional temperature gradients at a
140 seasonal scale. In this study, a new IM variation index was proposed to explore how
141 the TWS is related to atmospheric circulations and regional temperature gradients.
142 Given the close interaction between the IM and the western North Pacific monsoon
143 (WNPM) (e.g., Gu et al., 2010; Li and Hsu, 2018; Wang et al., 2001), the WNPM was
144 also considered to be a possible contributor to the TWS shifting. Furthermore, the
145 spatiotemporal variability of precipitation and the Palmer Drought Severity Index
146 were also explored because the PDSI represents the soil moisture state which is a
147 difference between precipitation and potential evapotranspiration.

148 Overall, the main objectives of this study are: (1) to evaluate spatio-temporal
149 characteristics of TWS associated with the other meteorological patterns in CIBA (2)
150 to quantify the relationships between the TWS variations and monsoons (i.e. the IM
151 and the WNPM); (3) to identify the temperature drivers related to monsoons and TWS
152 variations; and (4) to develop a framework for explaining the relationships of
153 temperature, monsoons and the TWS.

154 This study was organized as follows. A summary of various data sets and data
155 analysis approaches employed in this study were given in Section 2. The results were
156 given in Section 3, and they are followed by the corresponding discussion in Section 4.
157 In Section 5, the major findings and implications of shifting TWS over the CIBA were
158 summarized.



159
160 **Figure 1.** The general features (a) and Koppen climate types (b) of the CIBA. The
161 yellow and cyan shaded areas are Indus Basin and Ganges-Brahmaputra Basin
162 respectively in Figure 1a.

163 **2 Materials and methods**

164 2.1 Gravity Recovery and Climate Experiment (GRACE) data

165 The GRACE was designed to monitor the temporal and spatial variability of
166 the Earth's gravity field. Using the algorithm of Wahr et al. (1998), the gravity field
167 can be converted to the equivalent water height (EWH) for monitoring the TWS. In
168 this study, we used GRACE Level-2 Release 06 (RL06) from the Center for Space
169 Research (CSR; derived from <ftp://isdctftp.gfz-potsdam.de/grace/Level-2/CSR/RL06/>)
170 at University of Texas to explore the spatiotemporal dynamics of TWS over the CIBA,
171 in the form of Stokes spherical harmonic coefficients (SHCs) up to a degree and order
172 of 60. The TWS grid data derived from GRACE spans from April 2002 to March
173 2017 (total 15 years), with a spatial resolution of 1 degree and a global coverage. For
174 reducing the estimation errors of gravity anomalies, the pre-processing and
175 post-processing procedures for GRACE data were applied, and these procedures
176 include adding the degree-1 SHCs representing the geocenter motion (Swenson et al.,
177 2008), replacing of the C_{20} term with the results from Satellite Laser Ranging (SLR)
178 (Cheng and Ries, 2017), destripping, and applying the Gaussian filter with a radius of
179 350 km (Swenson and Wahr, 2006).

180 2.2 Meteorological data

181 For linking the TWS variation to precipitation pattern, the Tropical Rainfall
182 Measuring Mission (TRMM) 3B43 version 7 was used in this study. This TRMM
183 Multi-satellite Precipitation Analysis (TMPA) product were produced from

184 assimilating data from multiple precipitation satellites, radiometers, and rain gauges
185 by Huffman et al. (2007). The product was obtained from the NASA Goddard Space
186 Flight Center (<https://pmm.nasa.gov/data-access/downloads/trmm>), with a time span
187 ranging from 1998 to present, and a spatial coverage of 50°S-50°N with a resolution
188 of 0.25 degree.

189 Apart from the TWS and precipitation data, drought indices are used for
190 investigating the shift of hydrological conditions. In this study, the self-calibrating
191 Palmer drought severity index (PDSI) (Wells et al., 2004) was used due to its better
192 spatial comparability than traditional PDSI (Palmer, 1965), derived from the Research
193 Data Archive at National Center for Atmospheric Research (NCAR)
194 (<https://rda.ucar.edu/datasets/ds299.0/>) (Dai, 2017). The self-calibrating PDSI
195 (hereafter just called PDSI for simplicity) data ranges from 1850 to 2014 with a
196 monthly scale, covering the global land areas with a spatial resolution of 2.5 degree.

197 Other meteorological variables like the potential evaporation, snow melting
198 and temperature also play important roles in the hydrological dynamics. These
199 meteorological variables were derived from the ERA5-Land monthly averaged
200 datasets
201 (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=form>),
202 produced by the European Centre for Medium-Range Weather
203 Forecasts (ECMWF). The ERA5 datasets covers the period from 2001 to present, with
204 a high spatial resolution of $0.1 \times 0.1^\circ$. In addition, the sea surface temperature (SST)

205 [data are derived from the extended reconstructed SST version 5 \(ERSST.v5;](#)
206 <https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.ersst.v5.html>) of the National
207 [Climate Data Centre \(Huang et al., 2017\).](#)

208 2.3 Monsoon indices

209 The monsoon interaction zone of the IM and the WNPM is close to the edge
210 of our study area (i.e., the CIBA) over the Indochina Peninsula (Wang and LinHo,
211 2002). In order to quantify the effect of IM on the TWS variability over the CIBA, the
212 IM index was calculated, using the difference of zonal winds at 850-hPa between a
213 southern region (5°-15°N, 40°-80°E) and a northern region (20°-30°N, 70°-90°E)
214 (Wang et al., 2001). Based on the definition of Wang et al. (2001), the WNPM index
215 was also calculated, using the difference of zonal winds at 850-hPa a southern region
216 (5°-15°N, 100°-130°E) and a northern region (20°-30°N, 110°-140°E). The wind data
217 for the calculation of IM and WNPM indices were extracted from the National
218 Centers Environmental Prediction (NCEP) data (<https://www.ncep.noaa.gov/>).

219 2.4 Methodology

220 2.4.1 Moving standard deviation

221 Instead of using the conventional monsoon indices, we proposed to use the
222 moving standard deviation of monsoon indices, to examine how the monsoon
223 weakening affects the hydrological regimes over the CIBA. The moving standard
224 deviation of a given monsoon time series can be calculated as:

225
$$S(t) = \sqrt{\frac{\sum_{i=t}^{t+M} (x(i) - \mu(t))^2}{M - 1}} \quad (1)$$

226 where $S(t)$ and $\mu(t)$ represent the standard deviation and average value of
 227 monsoon index x for the period from t to $t + M$ at time t , respectively. M is the size
 228 of moving window, which is chosen as 12 months in this study. The time series
 229 formed by these standard deviations is hereafter called the monsoon variation index in
 230 this study.

231 2.4.2 Local Indicators of Spatial Association (LISA)

232 The LISA was proposed to measure the local association between one
 233 observations and its neighboring observations (Anselin, 1995). The general LISA for
 234 an observation Z_i at location i can be expressed as

235
$$L_i = f(Z_i, Z_{J_i}) \quad (2)$$

236 where f is a function for association calculation, and the Z_{J_i} are the observations at
 237 the neighboring locations J_i of i . In this study, we used Moran's I (Moran, 1950) to
 238 be the calculation function. The LISA based on Moran's I for location i can be
 239 written as

240
$$I_i = \frac{(Z_i - \bar{Z})}{S_i^2} \sum_{j=1, j \neq i}^n w_{ij} (Z_j - \bar{Z}) \quad (3)$$

241 where

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^n w_{ij}}{n - 1} - \bar{Z}^2$$

242 where n is the total number of observations, Z_i and Z_j are the observations at
243 location i and j ; w_{ij} is the spatial weight between location i and j .

244 2.4.3 Singular spectral analysis

245 To capture the spatiotemporal characteristics of the precipitation, the singular
246 spectral analysis (SSA) method was applied in this study. The SSA was introduced by
247 Broomhead and King (1986), aiming at decomposing a time series into a sum of
248 independent series identified as trend, periodic component, and noise (Hassani, 2007).
249 The decomposition process of the SSA can be divided into two steps: embedding and
250 singular value decomposition (SVD). Given a univariate time series $Y = (y_1, \dots, y_N)$,
251 the embedding procedure means transferring one dimensional Y into H -dimensional
252 vectors $\mathbf{X} = (X_1, \dots, X_H)$, where $X_i = (y_i, \dots, y_K)^T, i = 1, \dots, K = N - L + 1$. The
253 parameter $2 \leq L \leq N$ is the window length, and its selection is very important for
254 the SSA.

255 The covariance matrix \mathbf{C} should be firstly derived from the trajectory matrix
256 \mathbf{X} :

$$\mathbf{C} = \frac{1}{K} \mathbf{X}^T \mathbf{X} = \mathbf{E} \mathbf{\Lambda} \mathbf{E}^T$$

257 (4)

258 where $\mathbf{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_d)$, a diagonal matrix, consists of the eigenvalues of the
259 covariance matrix, and d is the rank of the \mathbf{X} . The matrix $\mathbf{E} = (\mathbf{e}_1, \dots, \mathbf{e}_d)$ includes
260 corresponding eigenvectors.

261 Based on the SVD, the trajectory matrix \mathbf{X} can be written as follows

262
$$\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \quad (5)$$

263 where the columns of \mathbf{U} and \mathbf{V} are orthogonal, containing the left and right
 264 eigenvectors of $\mathbf{X}\mathbf{\Sigma}$ is a diagonal matrix. Combined equation (1) and (2), the
 265 covariance matrix can be also denoted as

266
$$\mathbf{C} = \mathbf{U}(\mathbf{\Sigma}^2/K)\mathbf{U}^T \quad (6)$$

267 Thus $\mathbf{U} = (\mathbf{u}_1, \dots, \mathbf{u}_d) = \mathbf{E} = (\mathbf{e}_1, \dots, \mathbf{e}_d)$, $\mathbf{\Sigma} = \sqrt{K}\mathbf{\Lambda}^{1/2} = \text{diag}(\sqrt{K\lambda_1}, \dots, \sqrt{K\lambda_d})$,
 268 and $\mathbf{V} = (\mathbf{v}_1, \dots, \mathbf{v}_d)$ can also be easily obtained based on the equation (2). The \mathbf{u}_i
 269 and \mathbf{v}_i are called temporal empirical orthogonal functions (EOFs) and principal
 270 components (PCs), respectively.

271 In addition, the SVD of the trajectory matrix can be also written as

272
$$\mathbf{X} = \mathbf{X}_1 + \dots + \mathbf{X}_d \quad (7)$$

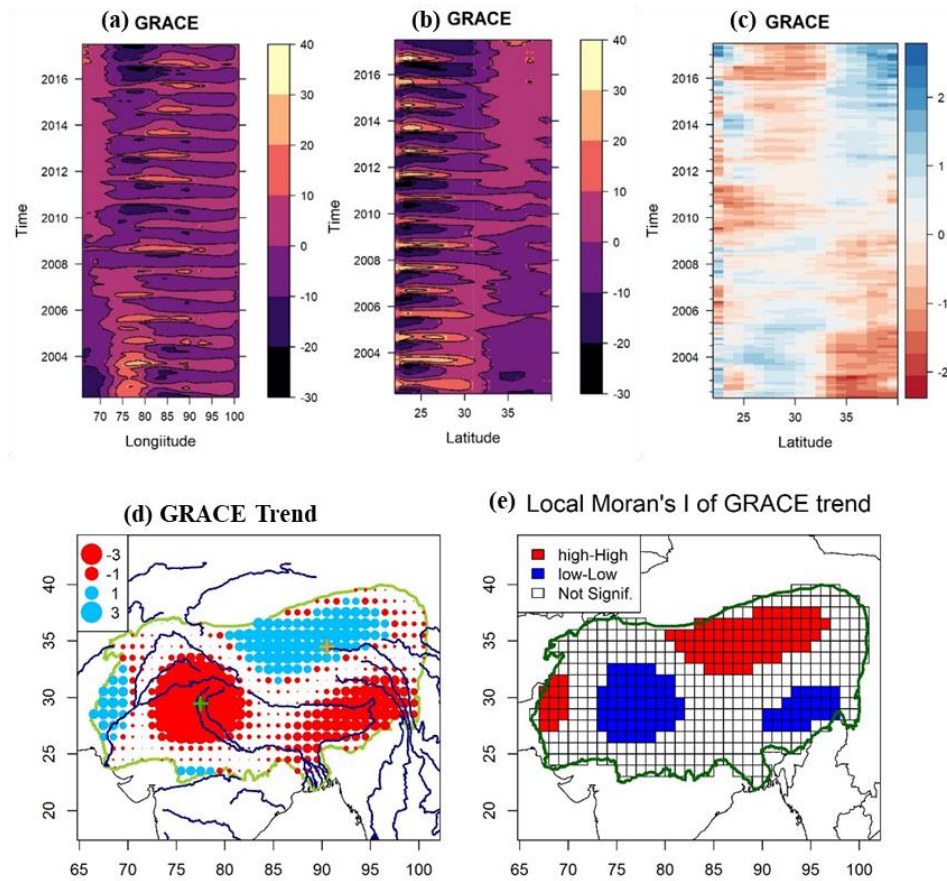
273 where $\mathbf{X}_i = \sqrt{K\lambda_i}\mathbf{u}_i\mathbf{v}_i^T$ ($i = 1, \dots, d$), are elementary matrices.

274 **3 Results**

275 **3.1 The water shifting characteristics**

276 Hovmöller diagrams (Hovmöller, 1949) were plotted to investigate the TWS
 277 spatiotemporal dynamic over the CIBA (66°E-101°E, 21°N-40°N) between 2002 and
 278 2017. According to the temporal variances of TWS along longitude and latitude,
 279 seasonal clusters were found along both longitude and latitude. Moreover, TWS
 280 showed an increasing trend over 80°E-90°E (the Chinese side) but a decreasing trend

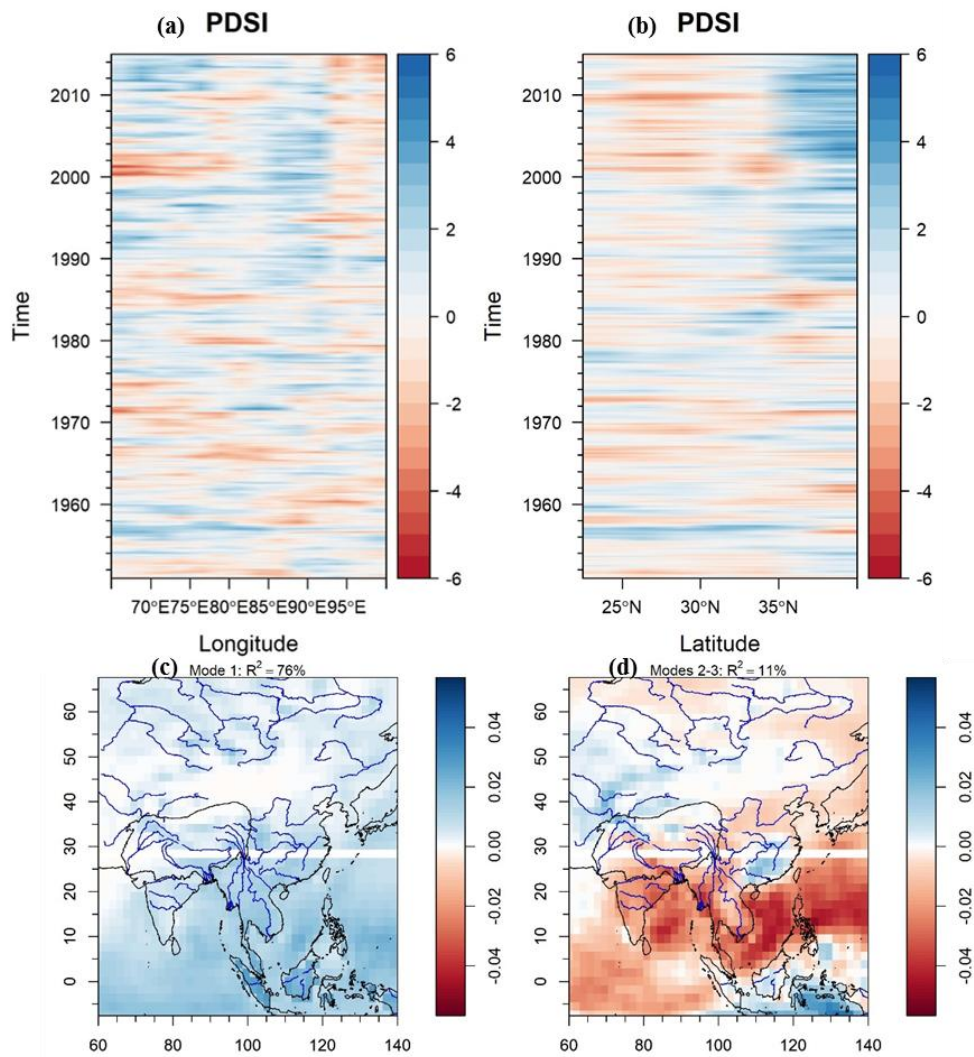
281 between 75°E and 80°E (the Indian side) (Figure 2a). In terms of latitude, the shift of
 282 TWS was even clearer. Figure 2b shows a decreasing trend between 28°N and 32°N
 283 and an increasing trend over 32°N-38°N. In order to get more apparent trend pattern,
 284 the Hovmöller diagram of seasonal TWS anomalies was shown in Figure 2c. It
 285 displays a distinctive increasing trend between 32°N and 38°N and a decreasing trend
 286 between 28°N and 32°N. The dividing line between increasing and decreasing trends
 287 was around the 32°N latitude.



288

289 **Figure 2.** Hovmöller diagrams of TWS (mm) along longitude (a) and latitude (b), and
290 the seasonal anomalies along latitude (c) over the CIBA region. Spatial trend
291 distribution of the TWS (d) and corresponding local Moran's I distribution (e) over
292 the CIBA. The blue and red circles represent the increasing and decreasing trend,
293 respectively. The orange and green crosses are the locations in western China and
294 northwestern India, respectively. The red and blue in (e) represent the high-high
295 hotspots and low-low hotspots respectively.

296 According to Figure 2a-c, the temporal TWS variances had clear spatial shifts
297 over the CIBA. Moreover, the spatial trend distribution of TWS and its LISA map
298 displayed three clusters (also called hot spots); two of them represented decreasing
299 trend, and one was increasing trend (Figure 2d-e). The increasing hot spot was located
300 at the region of 80°E-95°E, 32°N-37°N (i.e., western China), while decreasing hot
301 spots covered the regions of 72°E-82°E, 26°N-32°N (northwestern India) and
302 85°E-100°E, 25°N-31°N (Bangladesh, Figure 2d-e). The spatial trend pattern of TWS
303 was consistent with the Hovmöller diagrams of TWS (Figure 2a-c), indicating there
304 was a TWS shifting over the CIBA during 2002-2017.



305

306 **Figure 3.** Hovmöller diagrams of PDSI along longitude (a) and latitude (b) over the
 307 GBB. The mode 1 (c) and combination of mode 2 and mode 3 (d) of TRMM
 308 precipitation based on the SSA.

309 Apart from the TWS, the Hovmöller diagrams of TRMM derived-precipitation
 310 and PDSI were shown in Figure 3. The Hovmöller diagrams of PDSI showed that
 311 central QTP (87°E-92°E, 35°N-40°N) has been wetting (blue regions in the diagrams)

312 since the late 1980s (Figures 3a-b). After 2000, the northwestern India (26°N - 32°N)
313 has been drying (red regions in the diagram; Figure 3b). For precipitation, its seasonal
314 signals are very strong, which can mask the trend signals, leading to unclear
315 precipitation shifting pattern in the precipitation Hovmöller diagrams (not shown in
316 this paper). Therefore, we used SSA method to separate the seasonal and trend signals
317 (Figure 3c-d). The precipitation mode 1 represented the seasonal signal, which
318 accounts for 76% of the total variances. It explains 7 times of the variance explained
319 by the combination of mode 2 and mode 3 (hereafter called mode 2-3). The mode 2-3
320 accounts for 11% of the total precipitation variances, representing the secular trend
321 variances. It showed similar pattern with the spatial TWS trend distribution,
322 suggesting an increasing trend in western China and decreasing trend in other regions
323 of the GBB (Figure 3d).

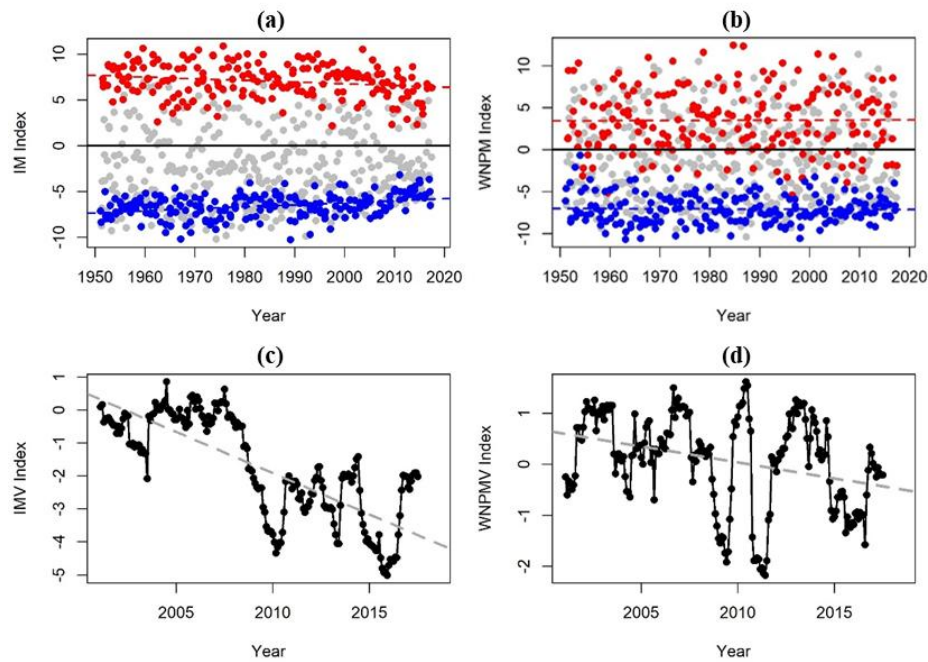
324 In addition, the potential evaporation distribution in Figure S1a showed a
325 drying-wetting trend pattern which is similar with that of the TWS. Changing TWS
326 over the IGBB during 2002-2017 can be directly caused by a more precipitation (and
327 less evaporation) trend over the central QTP and a precipitation decline (and
328 strengthened evaporation) over the IGBB (Figure 3d and Figure S1a). Similarly,
329 Figure S1b showed sharp declines of snow depths during 2002-2017 over the
330 northwest and the southeast corners of the QTP. These downward trends corresponded
331 well with the rising temperatures (Figure S1c). With the rising of the local
332 temperatures, a reducing snow depth trend (i.e., more snow melting) during
333 2002-2017 can be linked to increasing downstream surface waters such as the

334 expansion of lakes in the central QTP (Zhang et al., 2017). Therefore, for the QTP
335 region, the snow melting could be another important contributor to the TWS
336 variations.

337 In summary, the TWS water shifting pattern over the CIBA is wetting for the
338 western China and drying for the northwestern India. This shifting pattern could be
339 directly affected by precipitation, potential evaporation and snow melting, which are
340 mainly driven by the Asian monsoons modulated by regional temperature gradients.
341 Therefore, the impacts of Asian monsoons, including IM and WNPM, on the water
342 shifting since 2002 were investigated in next section.

343 3.2 Monsoon as a driving mechanism behind the TWS shifting

344 The summer IM index (for the months of JJA) had a decreasing trend, whereas
345 the winter IM index (for the months of DJF) had an increasing trend (Figure 4a).
346 However, for the monsoon intensity, the IM was weakening in both summer and
347 winter. Although it is less clear, the WNPM index showed similar weakening trend.
348 The weakening of the IM and WNPM could be the underlying drivers of water
349 shifting over the CIBA. To quantify this weakening effect, IM and WNPM variation
350 (hereafter called IMV and WNPMV) index were proposed based on the moving
351 standard deviation of the IM and WNPM index, showing the both IM and WNPM
352 strength were decreasing during 2002 and 2017 (Figure 4c-d). Particularly, the IMV
353 index fell abruptly since 2010.

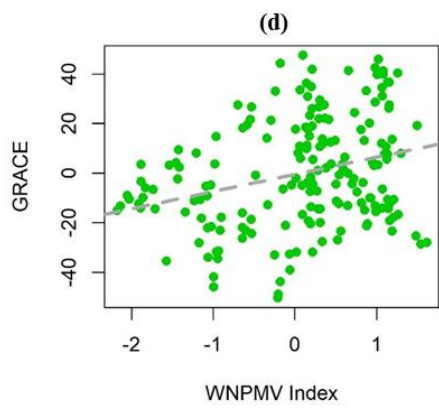
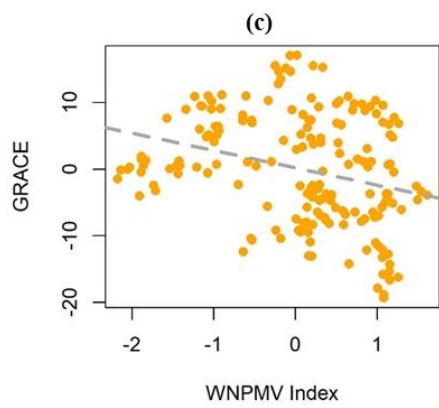
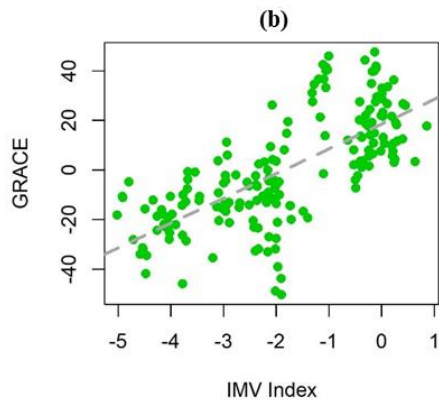
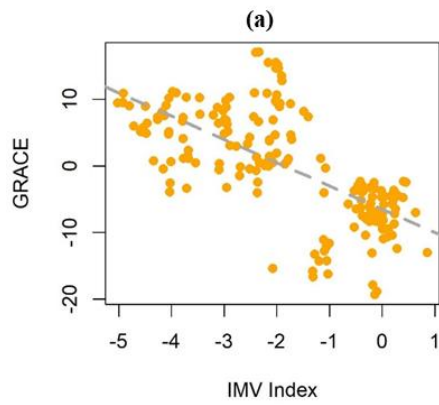


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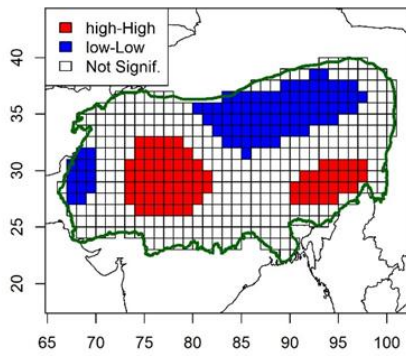
355 **Figure 4.** The monthly values of IM and WNPM indices during 1950-2017 (a-b) and
 356 the corresponding IMV and WNPMV indices during 2002-2017 (c-d). The red dots
 357 are the boreal summer (JJA) data and the blue dots are the winter (DJF) data in Figure
 358 4a and 4b.

359 For investigating the relationships between IM (and WNPM) and TWS over
 360 the CIBA, two TWS time series located in western China and northwestern India
 361 (orange and green cross respectively in Figure 2d) were extracted. There were no
 362 significant relationships between IM (and WNPM) and TWS in both the western
 363 China and northwestern India (Figure S2). However, a significant negative trend for
 364 the western China and a significant positive trend for the northwestern India between
 365 the IMV (and WNPMV) index and TWS were shown in Figure 5a-d. The results

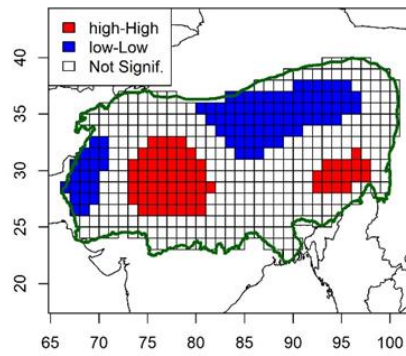
366 revealed that the weakening IM and WNPM could lead to an increasing TWS trend in
367 western China and a decreasing trend in northwestern India. Moreover, the LISA map
368 of the partial correlation of the IMV and TWS shared the similar pattern with that of
369 the WNPMV, showing significant negative and positive spatial clusters in western
370 China and northwestern India, respectively (Figure 5e-f), which was consistent with
371 the TWS trend patterns. Therefore, Figure 5a-f demonstrated that the TWS shifting
372 over the whole CIBA results from the weakening of the Asian monsoons. Additionally,
373 for the above-mentioned precipitation mode 2-3, representing the spatial precipitation
374 trend pattern, its temporal variation (hereafter called mode strength) was consistent
375 with the IMV and WNPMV step change (Figures S3), indicating that the precipitation
376 redistribution over the GBB was attributed to the IMV and WNPMV.



(e) Partial cor between GRACE and IMV



(f) Partial cor between GRACE and WNPMV



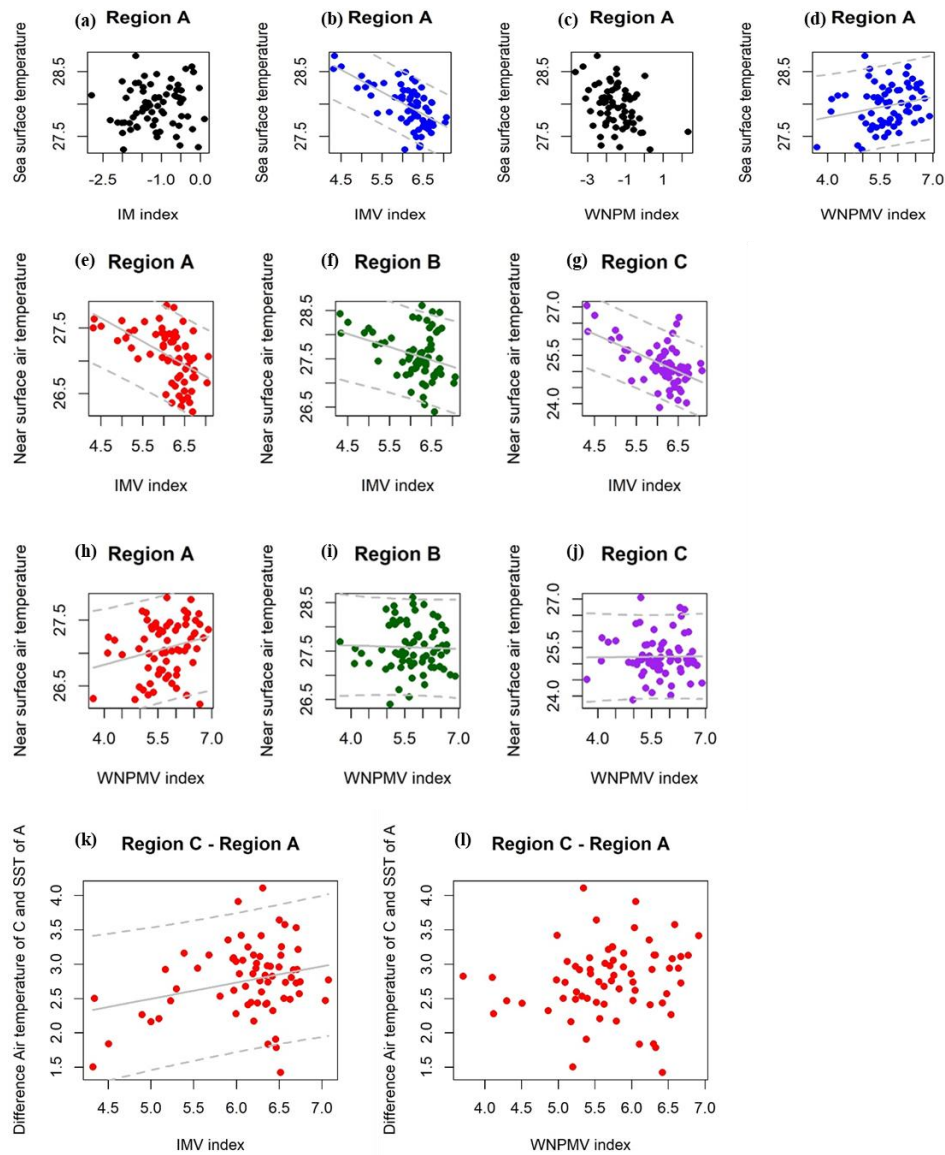
378 **Figure 5.** IMV and WNPMV against the TWS over the China (a, c) and India region
379 (b, d). The LISA map of partial correlation between TWS and IMV (e), and WNPMV
380 (f) over the CIBA.

381 3.3 Temperature drivers behind monsoons and TWS

382 The above results showed that the TWS shifting over the CIBA was caused by
383 the weakening of the IMV and WNPMV through modulating the precipitation
384 distribution. The IM and WNPM variability have been showed to be related to the sea
385 surface temperature (SST) (e.g., Annamalai et al., 2005; Weare, 1979; Xu et al., 2019),
386 the temperature of the QTP (e.g., Boos and Kuang, 2010; Zhao and Chen, 2001;
387 Zhisheng et al., 2015), and the land-ocean thermal difference (e.g., Roxy et al., 2015;
388 Tao et al., 2016; Yang et al., 2007). Therefore, to explore the relationship between
389 monsoons and surface temperatures, the average temperature over three regions
390 located in the Indian Ocean (hereafter called Region A), the Ganges (hereafter called
391 Region B) and the Brahmaputra (hereafter called Region C) were extracted (Figure
392 S4).

393 The Figure 6 showed the relationships between mean annual temperature in
394 different regions and monsoon indices for 70 years. Both the IM and WNPM indices
395 were not related to the mean SST of Region A (Figure 6a and 6c), while the IMV and
396 WNPMV fitted well with negative and positive relationship for the SST, respectively
397 (Figure 6b and 6d). Moreover, negative relationships between the IMV and the near
398 surface air temperature (NSAT) were found in all regions (Figure 6e-g). For the

399 WNPMV, it showed a positive relation with the NSAT at Region A, but negatively
400 correlated with the NASTs at Region B and Region C (Figure 6h-j). These outcomes
401 showed that the local and ocean temperature can modulate the monsoon variations.
402 The negative relationships between temperatures and the IMV at three regions
403 revealed that rising regional air temperatures and SST caused by increasing global
404 temperatures may be the driver of the IM weakening. In addition, the IMV had a
405 positively weak but statistically significant relationship with the thermal difference
406 between Region A and Region C, while the WNPMV showed no significant
407 relationship with the land-ocean thermal difference (Figures 6k-l), because it was
408 more likely related to the thermal difference between the Asian land surface and the
409 tropical Pacific Ocean based on its definition (Li and Hsu, 2018). Therefore, the
410 land-Indian Ocean thermal difference may play a weak role for changing monsoons
411 and thus the TWS spatial patterns.



412

413 **Figure 6.** IM, IMV, WNPM and WNPMV index against the SST in Region A (a-d);

414 IMV and WNPMV index against the NSAT in Region A, Region B and Region C (e-j);

415 IMV and WNPMV index against the air temperature difference between Region A and

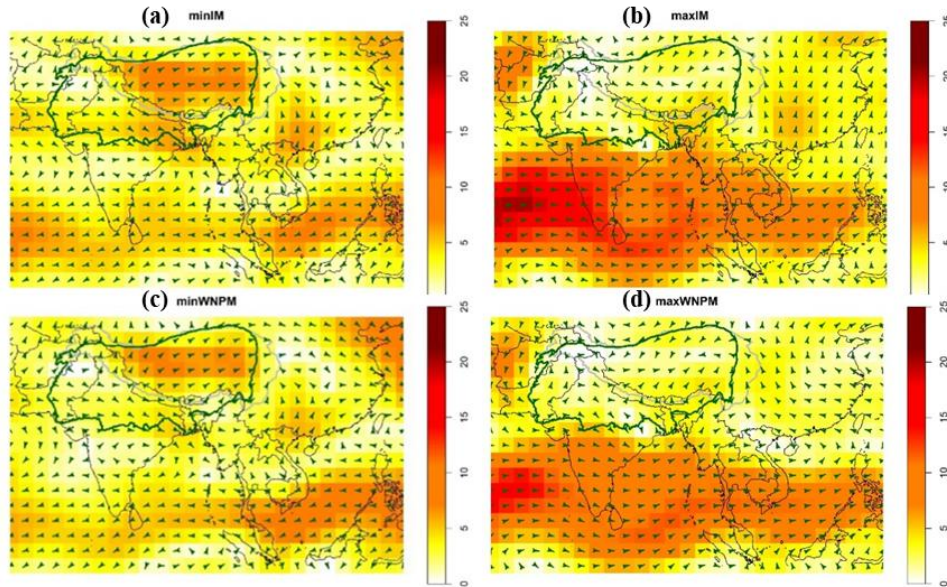
416 Region C (k-l).

417 **4 Discussion**

418 The TWS trend pattern and the Hovmöller diagrams clearly showed the spatial
419 clusters over the CIBA. There were (1) a significant decreasing cluster over the upper
420 Indus and Ganges (i.e., northwestern India), (2) an increasing cluster over the central
421 QTP (i.e., western China) and (3) a decreasing cluster over the southeastern
422 Brahmaputra basin (i.e., Bangladesh). In addition to decreasing precipitation and
423 increasing potential evaporation, the TWS decline in the IGBB was also probably
424 attributed to the over-exploitation of underground water for water supply in
425 agriculture and industrial sectors in northern India and Bangladesh (Rodell et al., 2009;
426 Shamsudduha et al., 2012). Given the TWS decline and population increase, the
427 IGBB region has now been facing severe water scarcity (Babel and Wahid, 2009), and
428 the situation will become more serious if no measure is taken.

429 Apart from the anthropogenic effect, the monsoon variability is a main natural
430 driver to the TWS shifting over the CIBA. Based on the monsoon variation analysis,
431 the weakening of the IMV and WNPMV were significant contributors to the
432 increasing TWS over the western China and the decreasing TWS over the
433 northwestern India. During winter (Figures 7a and 7c), less strong dry monsoon winds
434 come from the Himalaya over the Qinghai-Tibet Plateau; during summer (Figures 7b
435 and 7d), weak monsoons would bring less moist winds from the Arabian Sea to India.
436 Weaker and less moist winds would lead to drying windward side and wetting leeward

437 side of the Himalaya, and thus an increasing TWS over the western China and a
438 decreasing TWS over the northwestern India.

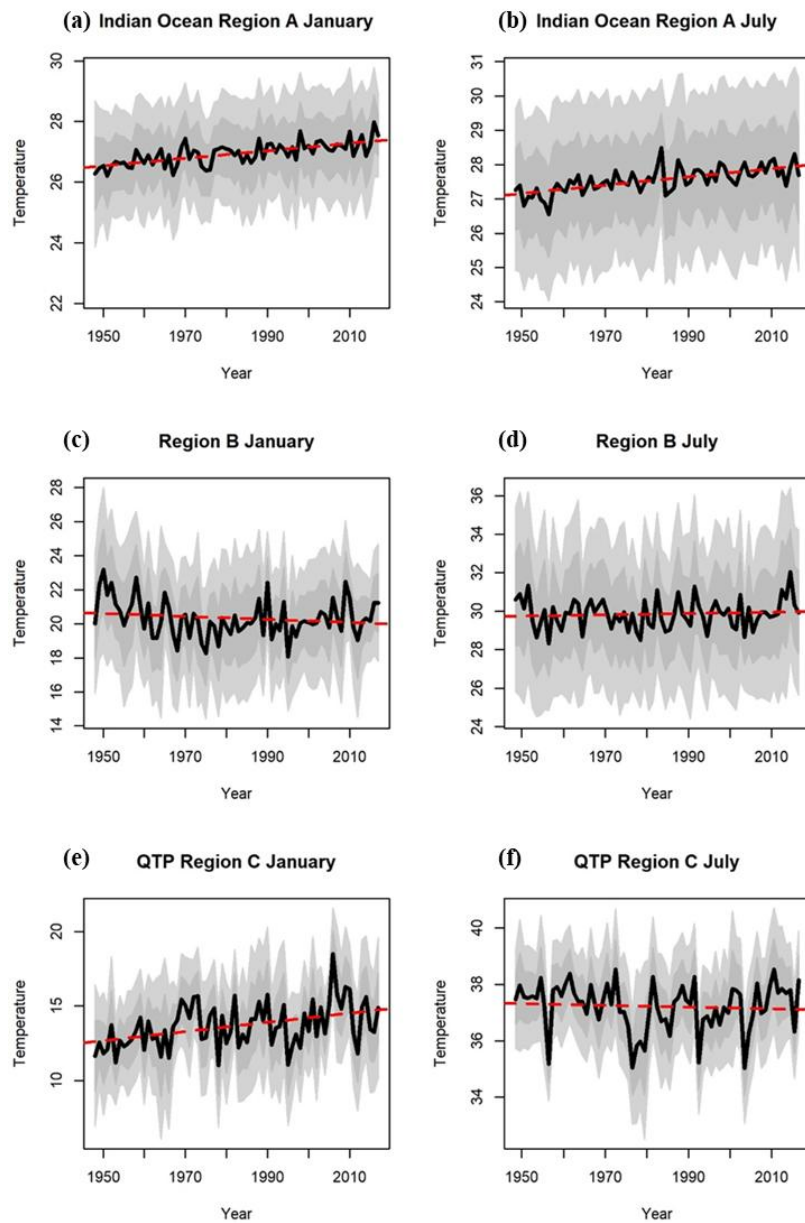


439

440 **Figure 7.** The average wind field of the lowest and highest 10% IM index (a-b),
441 representing the winter monsoons and summer monsoons, respectively. (c-d) are same
442 as (a-b) but for the WNP.

443 According to the Figures 8a-b, the Indian Ocean (Region A) had a clear
444 temperature increasing in both summer and winter. This temperature change led to the
445 weakening of the IM, based on the negative relationship between IMV and SST in
446 Region A (Figure 6b). The temperature over the Region B showed no obvious trend in
447 both summer and winter (Figures 8c-d). The QTP (Region C) showed an increasing
448 temperature trend in winter (Figure 8e), but no obvious trend in summer (Figure 8f).
449 The increasing trends of temperature over the Indian Ocean were larger than that over

450 the QTP in both winter and summer, indicating that the thermal difference between
451 the Indian Ocean and QTP was decreasing, leading to the decrease in the IM intensity
452 based on the positive relationship between IMV and temperature difference shown in
453 the Figure 6k. For the WNPMV, the increasing temperature over the Region A
454 indicated the strengthening of the WNPMV based on the positive relationship
455 between WNPMV and SST over Region A (Figure 6d). However, this result is not
456 consistent with the WNPMV weakening. This inconsistency can be explained by the
457 complex interactions between the Indian Ocean and the Pacific Ocean, and the
458 WNPM is less important for the CIBA, compared to the IM (Luo et al., 2010; 2012).



459

460 **Figure 8.** The average temperature variation over time in winter (January) and
 461 summer (July) over the Region A (a-b), Region B (c-d) and Region C (e-f).

462 **5 Conclusion**

463 In this study, we use the Hovmöller diagrams, the spatial TWS trend patterns
464 and their LISA maps to show that the TWS over the western China part was
465 increasing and the TWS over the northwestern India part was decreasing. The
466 precipitation and potential evaporation showed similar drying and wetting patterns
467 with the TWS, and snow melting due to the rising temperature can be an important
468 contributor to the TWS increase over western China (i.e., central QTP). The water
469 shifting pattern between 2002 and 2017 over the CIBA were controlled by the
470 changing Asian monsoon (i.e., IM and WNPM) and local temperature through the
471 modulation of precipitation, evaporation and snow melting.

472 The intensity of both IM and WNPM showed a gentle decreasing trend during
473 1950-2017. Furthermore, in order to emphasize the monsoon variation, IMV and
474 WNPMV were calculated based on the traditional monsoon indices, revealing that the
475 monsoon decreased dramatically during 2002-2017. In addition, the TWS over the
476 drying region (i.e., northwestern India) was positively correlated with IMV (and
477 WNPM), whereas the relationship between the TWS over the wetting zone (i.e.,
478 western China) and IMV (and WNPMV) was negative. This result suggested that the
479 weakening of the IM led to the decreasing and increasing trends of TWS over two
480 different regions of the CIBA. Moreover, similar clusters on the LISA maps further
481 show that the weakening monsoons caused the TWS redistribution over the CIBA.

482 Finally, the ocean and continental temperature difference changes modulated
483 the IM and WNPM variability, and they led to the TWS shifting over the CIBA. The
484 temperatures over the QTP, the Ganges, and the Indian Ocean were negatively
485 correlated with the IMV, indicating that increasing local temperatures weakened the
486 IM, and thus affecting the TWS shifting. Meanwhile, the decrease in the thermal
487 difference between the QTP and the Indian Ocean can also explain the weakening of
488 the IM because of their positive relationship.

489 In this study, we looked at monsoon roles for changing TWS. Although the
490 Glacial Isostatic Adjustment (GIA) were applied to the TWS data, the glacier effect
491 can be important for explaining the observed TWS shifts. The observed drying center
492 at the headwater of the Ganges can be related to the Gangotri glacier which is one of
493 the largest glaciers in the Himalayas. The Gangotri glacier has been retreating at a
494 significant rate between 22 and 27 m/year (Bhambri et al., 2011; Jain, 2008). The
495 glacier retreat could be another explanation of decreasing TWS over the Ganges due
496 to the temperature changes.

497 In summary, our findings have linked spatial water shifting over the CIBA to
498 monsoon variations and changing local or even global temperature gradients. The
499 main limitation of the study is whether the detected TWS shifting will last after 2017.
500 For future studies, it will be worthwhile to project future TWS distributions using the
501 temperature gradients derived from climate model outputs based on different
502 Representative Concentration Pathways (RCPs). Then, these projected water

503 conditions can help decision-makers to propose water management designs, including
504 (1) establishing water consumption quotas for regions having declining TWS and (2)
505 setting up flood control measures for places having increasing TWS. Therefore, the
506 dynamic relationships between temperature gradient, TWS and monsoons in this
507 study is not only building blocks for exploring the mechanisms of shifting
508 hydroclimatic systems, but also providing new insights for future water management
509 designs to the region.

510 **Acknowledgments**

511 This research was funded by the Hong Kong Baptist University Faculty research Fund
512 (FRG1/1617/005, FRG2/1617/082, FRG2/1516/085), ~~and~~ the National Natural Science
513 Foundation of China (NSFC) (Grant No. 41974003, 41674007), and The Scientific and
514 Technological Research Council of Turkey (TUBITAK) 2232 grant (118C329). This
515 research was conducted using the resources of the High Performance Cluster
516 Computing Centre, Hong Kong Baptist University, which receives funding from
517 Research Grant Council, University Grant Committee of the HKSAR and Hong Kong
518 Baptist University. The datasets used in this study are publicly available, and the
519 corresponding URLs are provided in the section 2.

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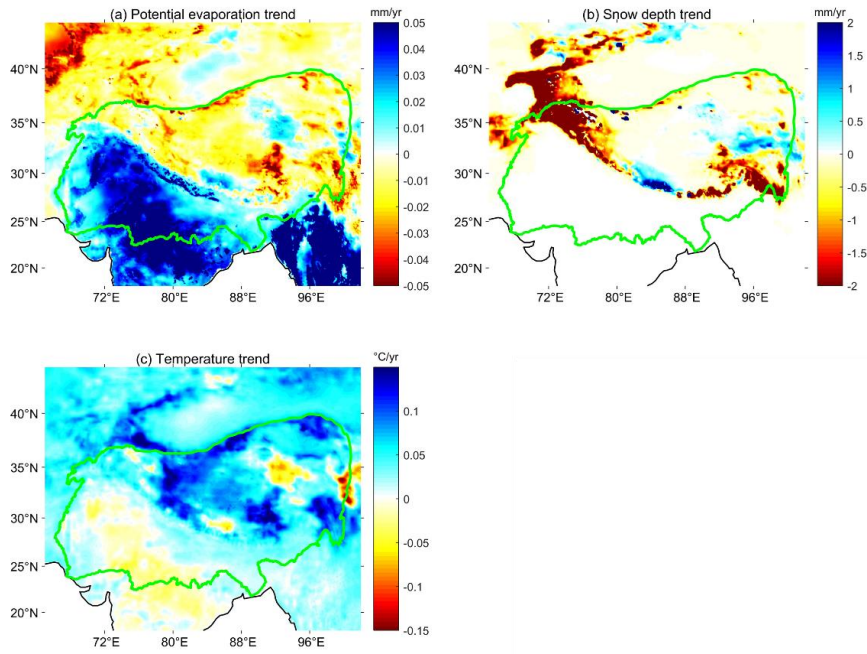
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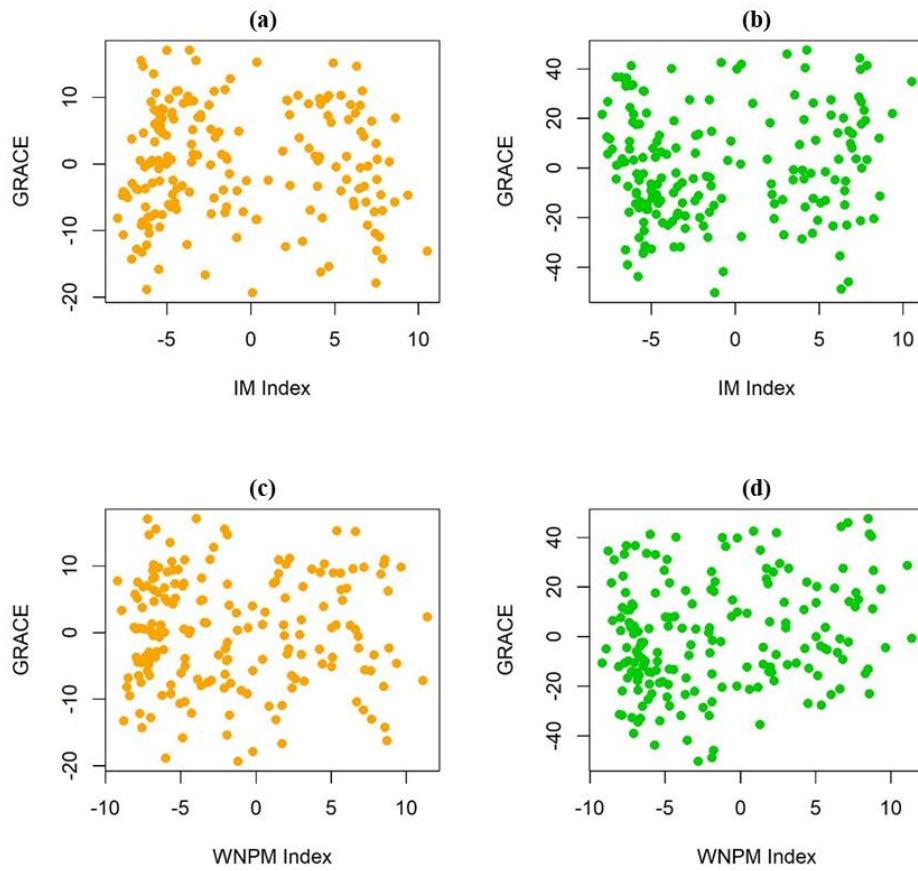
720 **Appendix**



721

722 **Figure S1.** The potential evaporation (a), snow depth (b) and temperature trend (c) pattern over

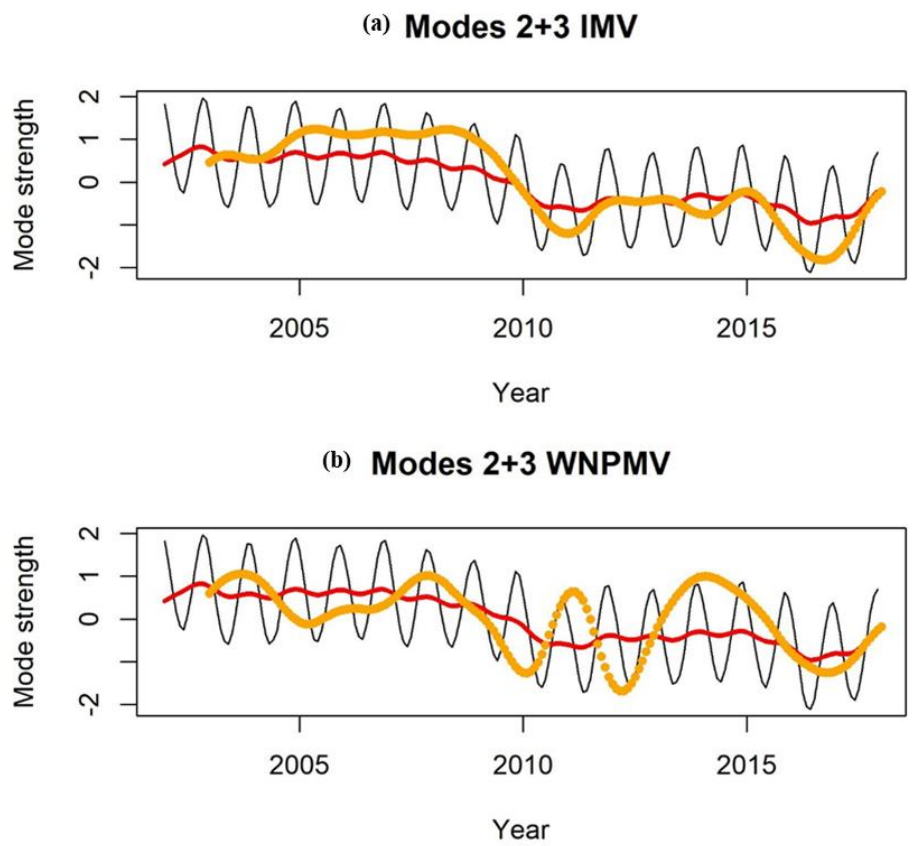
723 the CIBA.



724

725 **Figure S2.** The IM and WNPM index against the TWS over the China (a, c) and India

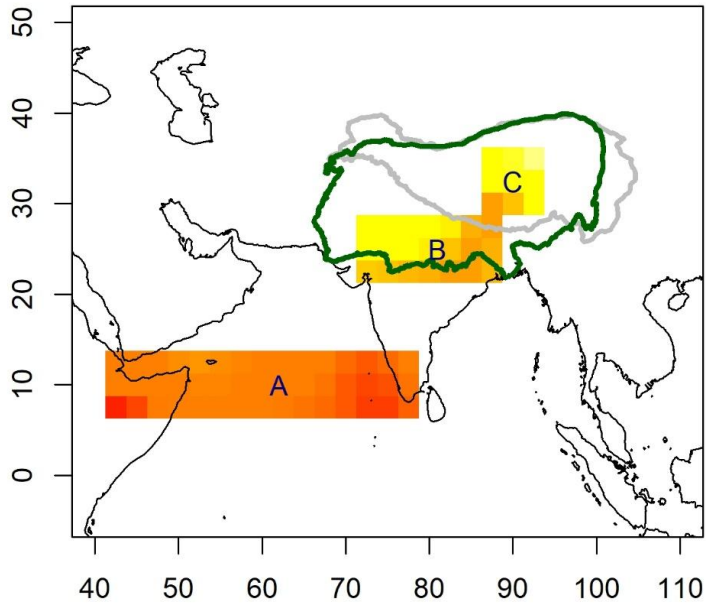
726 region (b, d) of CIBA.



727

728 **Figure S3.** The mode strength of precipitation mode 2-3 (red) against the IMV (a) and

729 WNPM step change (orange) (b).



730

731 **Figure S4.** The selected temperature locations.

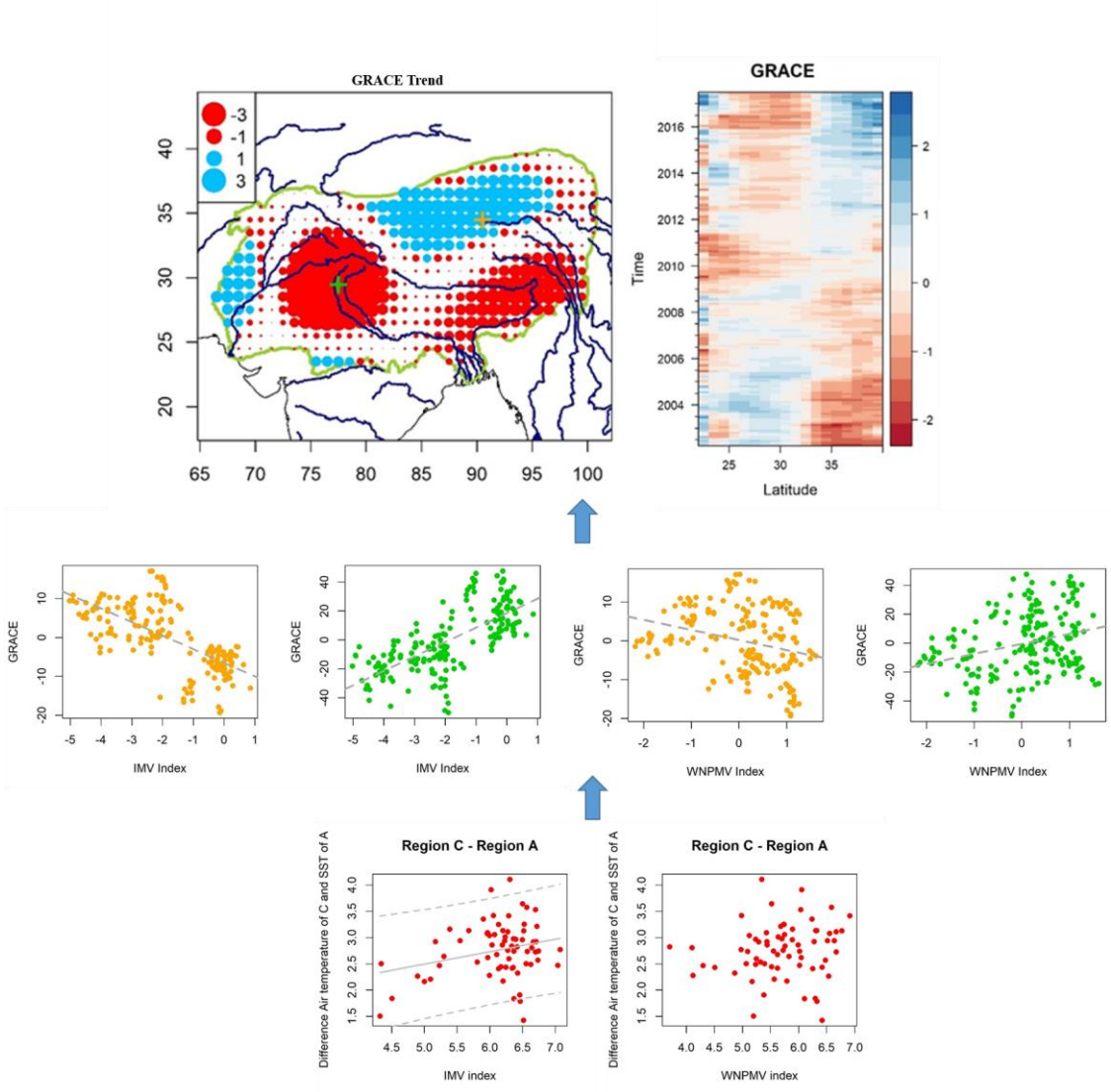
732

*Graphical Abstract

Water shifting

Monsoon variation weakening

Decreasing temperature gradient



Highlights:

- Terrestrial water storage showed a clear shifting pattern
- Pattern showed wetting in western China and drying in northwestern India.
- The shifting patterns were mainly due to the weakening of the monsoon variations.
- Weakening monsoon were related to decreasing regional temperature gradients.

1 **Gravimetry-based water storage shifting over the China-India border area**
2 **controlled by regional climate variability**

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19 **Highlights:**

- 20 • Terrestrial water storage showed a clear shifting pattern
- 21 • Pattern showed wetting in western China and drying in northwestern India.
- 22 • The shifting patterns were mainly due to the weakening of the monsoon
- 23 variations.
- 24 • Weakening monsoon were related to decreasing regional temperature gradients.

25 **Abstract**

26 The regional water storage shifting causes nonstationary spatial distribution of droughts
27 and flooding, leading to water management challenges, environmental degradation and
28 economic losses. The regional water storage shifting is becoming evident due to the
29 increasing climate variability. However, the previous studies for climate drivers behind
30 the water storage shifting are not rigorously quantified. In this study, the terrestrial
31 water storage (TWS) spatial shifting pattern during 2002-2017 over the China-India
32 border area (CIBA) is developed using the Gravity Recovery and Climate Experiment
33 (GRACE), suggesting that the northwestern India were wetting while western China
34 was drying. Similar drying and wetting patterns were also found in the precipitation,
35 snow depth, Palmer Drought Severity Index (PDSI) and potential evaporation data.
36 Based on our newly proposed Indian monsoon (IM) and western North Pacific
37 monsoon (WNPM) variation indices, the water shifting pattern over the CIBA was
38 found to be affected by the weakening of the variation of IM and WNPM through
39 modulating the regional atmospheric circulation. The weakening of IM and WNPM

40 variations has shown to be attributed to the decreasing temperature gradient between
41 the CIBA and the Indian Ocean, and possibly related to increasing regional
42 temperatures associated with the increasing global temperature. As the global warming
43 intensifies, it is expected that the regional TWS shifting pattern over the CIBA will be
44 further exaggerated, stressing the need of advancing water resources management for
45 local communities in the region.

46 **Keywords**

47 Water storage shifting; Gravity Recovery and Climate Experiment; climate variability;
48 China-India border area

49 **1 Introduction**

50 Terrestrial water storage (TWS), including canopy water, glaciers, snow,
51 surface water in rivers, lakes, wetlands and reservoirs, and underground water,
52 determines global and regional hydrological resilience (Alsdorf et al., 2007). It plays a
53 major role in the exchange of water with the atmosphere and oceans, and affects
54 climate variability (Kim et al., 2009). Therefore, the TWS monitoring as well as the
55 underlying drivers for its spatiotemporal dynamics are crucial for understanding the
56 climatic-hydrological system (Humphrey et al., 2016). With the launch of the Gravity
57 Recovery and Climate Experiment (GRACE) in March 2002, it provides a novel and
58 reliable tool for TWS monitoring (e.g., Long et al., 2015; Long et al., 2017; Reager
59 and Famiglietti, 2009b; Scanlon et al., 2019; Schmidt et al., 2006b; Sinha et al., 2016;
60 Syed et al., 2008; Tapley et al., 2004).

61 In recent years, the GRACE data has been widely used to assess the TWS
62 variability (e.g., Güntner et al., 2007; Long et al., 2015; Schmidt et al., 2006a), to
63 monitor droughts (e.g., Houborg et al., 2012; Thomas et al., 2014; Yi and Wen, 2016;
64 Zhao et al., 2017) and flooding (e.g., Chen et al., 2010; Reager and Famiglietti, 2009a;
65 Reager et al., 2014); it is also used to evaluate groundwater depletion (e.g., Long et al.,
66 2016; Rodell et al., 2009; Thomas and Famiglietti, 2019), and to estimate ice sheet or
67 glacier loss (e.g., Chen et al., 2009; Farinotti et al., 2015; Shepherd et al., 2018).
68 These studies have demonstrated the capability of GRACE to observe regional
69 hydrological variability and global climate abnormalities, which are used for
70 investigated water cycles linked with global and regional climates. For investigating
71 the GRACE long-term trend variability, Rodell et al. (2018) quantified the global
72 TWS trends during 2002-2016 and provided their corresponding causes. They found a
73 general wetting pattern at high- and low-latitudes and a drying pattern at mid-latitudes,
74 and these patterns are mainly due to the regular natural variability, groundwater
75 depletion, and climate change. Meanwhile, Scanlon et al. (2018) found the TWS in
76 some mid-latitude basins were decreasing, including Arkansas, Indus, Ganges,
77 Brahmaputra, Hai River, Euphrates. On the other hand, high- and low-latitude regions
78 showed an increasing TWS trend including Missouri, Amazon, Okavango, and
79 Murray basin.

80 The increasing water loss at mid-latitudes exerts great pressure on the water
81 supply in mid-latitude countries, in particular populous China and India. The
82 China-India border area (CIBA, Figure 1), covering the Qinghai-Tibet Plateau (QTP),

83 and Indus-Ganges-Brahmaputra basin (IGBB), is shared by multiple nations,
84 including China, India, Nepal, Bhutan, Bangladesh, and Pakistan. The Tibetan Plateau,
85 known as the ‘third pole’ of the Earth (Yao et al., 2012), affects regional thermal
86 gradients which modulate local circulations (Duan et al., 2018; Wu et al., 2014; Zhao
87 and Chen, 2001). Therefore, exploring how local climate mechanisms affect the TWS
88 variability over the CIBA can provide information to decision makers for managing
89 water resources shared among multiple populous nations. Over the IGBB, there have
90 been several studies focusing on the water storage variations over the IGBB (e.g.,
91 Khandu et al., 2016; Scanlon et al., 2018) and QTP regions (e.g., Song et al., 2015;
92 Xiang et al., 2016; Zhang et al., 2017). Related to the glacial processes, sharp water
93 mass losses were observed in the southeast QTP between 2003 and 2011 (Song et al.,
94 2015). Moreover, the lake volume in QTP region increased from 1970s to 2015
95 (Zhang et al., 2017). Over the IGBB, the TWS declined rapidly due to decreasing
96 precipitation during 2002-2014 (Khandu et al., 2016) and increasing irrigation
97 (Scanlon et al., 2018). Overall, previous studies clearly showed the separate trend
98 variations of TWS in QTP and IGBB. Although they attempted to explain the TWS
99 variations using meteorological forcing (e.g. precipitation and temperature) and
100 human influences (e.g. irrigation), the TWS variations over the IGBB can be
101 associated with the water conditions over the QTP, since the headwaters of the Indus,
102 Ganges and Brahmaputra rivers originate in the QTP region (Kuehl et al., 2011).
103 Therefore, there is a need to investigate the TWS dynamic in the QTP and the IGBB
104 as an integral system rather than individual separate components. Furthermore, the

105 TWS variations are not only directly controlled by the local precipitation and
106 temperature, but also indirectly affected by regional atmospheric circulations and
107 temperature gradients between land and ocean.

108 Over the IGBB, the spatiotemporal dynamic of the hydrological regime is
109 mainly under the control of the Indian monsoon (IM) (Khandu et al., 2017). Over the
110 IGBB from July to September, the IM contributes to around 60-90% of the annual
111 precipitation (Khandu et al., 2016). Due to the complex climate types, (Figure 1b), the
112 IGBB has unevenly distributed precipitation over the sub-basins. In the Ganges basin,
113 the northwest region is dryer than the coast area; in the Brahmaputra basin, there is
114 heavy precipitation because of the rain shadow effect (Mirza et al., 1998). The upper
115 Indus basin receives more precipitation than the lower basin, especially in the
116 mountain region (Archer et al., 2010). Furthermore, the formation and variation of the
117 IM are closely related to the QTP heating (Feng and Hu, 2005; Molnar et al., 1993;
118 Sato and Kimura, 2007), and the IM affects precipitation patterns and river
119 distributions over the QTP (Yao et al., 2009). Therefore, the IM plays an crucial role
120 in the water dynamics over the whole CIBA.

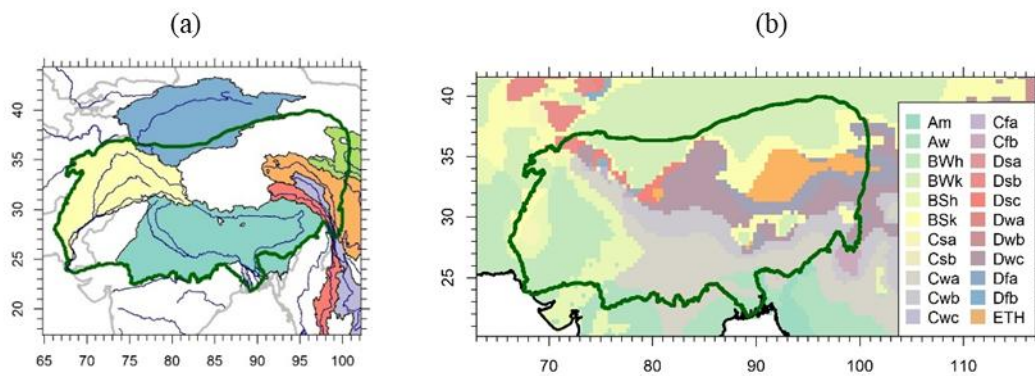
121 Apart from the influence of IM, the regional temperature gradient could be an
122 indirect contributor to the hydrological variability over the IGBB region. For instance,
123 Roxy et al. (2015) found that the decreasing land-sea thermal gradient weakens the
124 summer monsoon circulation and leads to the rainfall variations in India, due to rapid
125 Indian Ocean warming. Over the past decades, the regional temperature increase

126 caused wetter conditions in central and northern QTP (Yang et al., 2014). Moreover,
127 changing hydroclimatic extreme events over the QTP and IGBB region are suggested
128 to be related to shifting atmospheric and hydrological patterns due to increasing
129 global average temperatures (Wijngaard et al., 2017). In recent years, more frequent
130 droughts occurred in central India (Mallya et al., 2016; Rajeevan and Bhate, 2009),
131 Nepal (Baidya et al., 2008), and Bangladesh (Shahid, 2011), while the extreme
132 precipitation events were increased over the most parts of the India (Roxy et al., 2017;
133 Sen Roy and Balling, 2004). In the central QTP, grasslands were affected by flooding
134 due to the expansion of the surrounding lakes since the early 2000s (Zhu et al., 2010).

135 Over the CIBA, the changes of precipitation driven by IM variability affect the
136 TWS dynamic (e.g., Khandu et al., 2016; Papa et al., 2010; 2015). The relationships
137 between the IM and the TWS over the CIBA were only discussed qualitatively in
138 almost all previous studies, but few studies have quantified these relationships and
139 analyzed their mechanisms associated with regional temperature gradients at a
140 seasonal scale. In this study, a new IM variation index was proposed to explore how
141 the TWS is related to atmospheric circulations and regional temperature gradients.
142 Given the close interaction between the IM and the western North Pacific monsoon
143 (WNPM) (e.g., Gu et al., 2010; Li and Hsu, 2018; Wang et al., 2001), the WNPM was
144 also considered to be a possible contributor to the TWS shifting. Furthermore, the
145 spatiotemporal variability of precipitation and the Palmer Drought Severity Index
146 were also explored because the PDSI represents the soil moisture state which is a
147 difference between precipitation and potential evapotranspiration.

148 Overall, the main objectives of this study are: (1) to evaluate spatio-temporal
149 characteristics of TWS associated with the other meteorological patterns in CIBA (2)
150 to quantify the relationships between the TWS variations and monsoons (i.e. the IM
151 and the WNPM); (3) to identify the temperature drivers related to monsoons and TWS
152 variations; and (4) to develop a framework for explaining the relationships of
153 temperature, monsoons and the TWS.

154 This study was organized as follows. A summary of various data sets and data
155 analysis approaches employed in this study were given in Section 2. The results were
156 given in Section 3, and they are followed by the corresponding discussion in Section 4.
157 In Section 5, the major findings and implications of shifting TWS over the CIBA were
158 summarized.



159
160 **Figure 1.** The general features (a) and Koppen climate types (b) of the CIBA. The
161 yellow and cyan shaded areas are Indus Basin and Ganges-Brahmaputra Basin
162 respectively in Figure 1a.

163 **2 Materials and methods**

164 2.1 Gravity Recovery and Climate Experiment (GRACE) data

165 The GRACE was designed to monitor the temporal and spatial variability of
166 the Earth's gravity field. Using the algorithm of Wahr et al. (1998), the gravity field
167 can be converted to the equivalent water height (EWH) for monitoring the TWS. In
168 this study, we used GRACE Level-2 Release 06 (RL06) from the Center for Space
169 Research (CSR; derived from <ftp://isdcftp.gfz-potsdam.de/grace/Level-2/CSR/RL06/>)
170 at University of Texas to explore the spatiotemporal dynamics of TWS over the CIBA,
171 in the form of Stokes spherical harmonic coefficients (SHCs) up to a degree and order
172 of 60. The TWS grid data derived from GRACE spans from April 2002 to March
173 2017 (total 15 years), with a spatial resolution of 1 degree and a global coverage. For
174 reducing the estimation errors of gravity anomalies, the pre-processing and
175 post-processing procedures for GRACE data were applied, and these procedures
176 include adding the degree-1 SHCs representing the geocenter motion (Swenson et al.,
177 2008), replacing of the C_{20} term with the results from Satellite Laser Ranging (SLR)
178 (Cheng and Ries, 2017), destripping, and applying the Gaussian filter with a radius of
179 350 km (Swenson and Wahr, 2006).

180 2.2 Meteorological data

181 For linking the TWS variation to precipitation pattern, the Tropical Rainfall
182 Measuring Mission (TRMM) 3B43 version 7 was used in this study. This TRMM
183 Multi-satellite Precipitation Analysis (TMPA) product were produced from

184 assimilating data from multiple precipitation satellites, radiometers, and rain gauges
185 by Huffman et al. (2007). The product was obtained from the NASA Goddard Space
186 Flight Center (<https://pmm.nasa.gov/data-access/downloads/trmm>), with a time span
187 ranging from 1998 to present, and a spatial coverage of 50°S-50°N with a resolution
188 of 0.25 degree.

189 Apart from the TWS and precipitation data, drought indices are used for
190 investigating the shift of hydrological conditions. In this study, the self-calibrating
191 Palmer drought severity index (PDSI) (Wells et al., 2004) was used due to its better
192 spatial comparability than traditional PDSI (Palmer, 1965), derived from the Research
193 Data Archive at National Center for Atmospheric Research (NCAR)
194 (<https://rda.ucar.edu/datasets/ds299.0/>) (Dai, 2017). The self-calibrating PDSI
195 (hereafter just called PDSI for simplicity) data ranges from 1850 to 2014 with a
196 monthly scale, covering the global land areas with a spatial resolution of 2.5 degree.

197 Other meteorological variables like the potential evaporation, snow melting
198 and temperature also play important roles in the hydrological dynamics. These
199 meteorological variables were derived from the ERA5-Land monthly averaged
200 datasets
201 (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=form>), produced by the European Centre for Medium-Range Weather
202 Forecasts (ECMWF). The ERA5 datasets covers the period from 2001 to present, with
203 a high spatial resolution of $0.1 \times 0.1^\circ$. In addition, the sea surface temperature (SST)
204

205 data are derived from the extended reconstructed SST version 5 (ERSST.v5;
206 <https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.ersst.v5.html>) of the National
207 Climate Data Centre (Huang et al., 2017).

208 2.3 Monsoon indices

209 The monsoon interaction zone of the IM and the WNPM is close to the edge
210 of our study area (i.e., the CIBA) over the Indochina Peninsula (Wang and LinHo,
211 2002). In order to quantify the effect of IM on the TWS variability over the CIBA, the
212 IM index was calculated, using the difference of zonal winds at 850-hPa between a
213 southern region (5°-15°N, 40°-80°E) and a northern region (20°-30°N, 70°-90°E)
214 (Wang et al., 2001). Based on the definition of Wang et al. (2001), the WNPM index
215 was also calculated, using the difference of zonal winds at 850-hPa a southern region
216 (5°-15°N, 100°-130°E) and a northern region (20°-30°N, 110°-140°E). The wind data
217 for the calculation of IM and WNPM indices were extracted from the National
218 Centers Environmental Prediction (NCEP) data (<https://www.ncep.noaa.gov/>).

219 2.4 Methodology

220 2.4.1 Moving standard deviation

221 Instead of using the conventional monsoon indices, we proposed to use the
222 moving standard deviation of monsoon indices, to examine how the monsoon
223 weakening affects the hydrological regimes over the CIBA. The moving standard
224 deviation of a given monsoon time series can be calculated as:

225
$$S(t) = \sqrt{\frac{\sum_{i=t}^{t+M} (x(i) - \mu(t))^2}{M-1}} \quad (1)$$

226 where $S(t)$ and $\mu(t)$ represent the standard deviation and average value of
 227 monsoon index x for the period from t to $t + M$ at time t , respectively. M is the size
 228 of moving window, which is chosen as 12 months in this study. The time series
 229 formed by these standard deviations is hereafter called the monsoon variation index in
 230 this study.

231 2.4.2 Local Indicators of Spatial Association (LISA)

232 The LISA was proposed to measure the local association between one
 233 observations and its neighboring observations (Anselin, 1995). The general LISA for
 234 an observation Z_i at location i can be expressed as

235
$$L_i = f(Z_i, Z_{J_i}) \quad (2)$$

236 where f is a function for association calculation, and the Z_{J_i} are the observations at
 237 the neighboring locations J_i of i . In this study, we used Moran's I (Moran, 1950) to
 238 be the calculation function. The LISA based on Moran's I for location i can be
 239 written as

240
$$I_i = \frac{(Z_i - \bar{Z})}{S_i^2} \sum_{j=1, j \neq i}^n w_{ij} (Z_j - \bar{Z}) \quad (3)$$

241 where

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^n w_{ij} (Z_j - \bar{Z})^2}{n-1} - \bar{Z}^2$$

242 where n is the total number of observations, Z_i and Z_j are the observations at
243 location i and j ; w_{ij} is the spatial weight between location i and j .

244 2.4.3 Singular spectral analysis

245 To capture the spatiotemporal characteristics of the precipitation, the singular
246 spectral analysis (SSA) method was applied in this study. The SSA was introduced by
247 Broomhead and King (1986), aiming at decomposing a time series into a sum of
248 independent series identified as trend, periodic component, and noise (Hassani, 2007).
249 The decomposition process of the SSA can be divided into two steps: embedding and
250 singular value decomposition (SVD). Given a univariate time series $Y = (y_1, \dots, y_N)$,
251 the embedding procedure means transferring one dimensional Y into H -dimensional
252 vectors $\mathbf{X} = (X_1, \dots, X_H)$, where $X_i = (y_i, \dots, y_K)^T$, $i = 1, \dots, K = N - L + 1$. The
253 parameter $2 \leq L \leq N$ is the window length, and its selection is very important for
254 the SSA.

255 The covariance matrix C should be firstly derived from the trajectory matrix
256 \mathbf{X} :

$$C = \frac{1}{K} \mathbf{X}^T \mathbf{X} = \mathbf{E} \mathbf{\Lambda} \mathbf{E}^T \quad (4)$$

258 where $\mathbf{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_d)$, a diagonal matrix, consists of the eigenvalues of the
259 covariance matrix, and d is the rank of the \mathbf{X} . The matrix $\mathbf{E} = (\mathbf{e}_1, \dots, \mathbf{e}_d)$ includes
260 corresponding eigenvectors.

261 Based on the SVD, the trajectory matrix \mathbf{X} can be written as follows

262
$$\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \quad (5)$$

263 where the columns of \mathbf{U} and \mathbf{V} are orthogonal, containing the left and right
 264 eigenvectors of $\mathbf{X}, \mathbf{\Sigma}$ is a diagonal matrix. Combined equation (1) and (2), the
 265 covariance matrix can be also denoted as

266
$$\mathbf{C} = \mathbf{U}(\mathbf{\Sigma}^2/K)\mathbf{U}^T \quad (6)$$

267 Thus $\mathbf{U} = (\mathbf{u}_1, \dots, \mathbf{u}_d) = \mathbf{E} = (\mathbf{e}_1, \dots, \mathbf{e}_d)$, $\mathbf{\Sigma} = \sqrt{K}\mathbf{\Lambda}^{1/2} = \text{diag}(\sqrt{K\lambda_1}, \dots, \sqrt{K\lambda_d})$,
 268 and $\mathbf{V} = (\mathbf{v}_1, \dots, \mathbf{v}_d)$ can also be easily obtained based on the equation (2). The \mathbf{u}_i
 269 and \mathbf{v}_i are called temporal empirical orthogonal functions (EOFs) and principal
 270 components (PCs), respectively.

271 In addition, the SVD of the trajectory matrix can be also written as

272
$$\mathbf{X} = \mathbf{X}_1 + \dots + \mathbf{X}_d \quad (7)$$

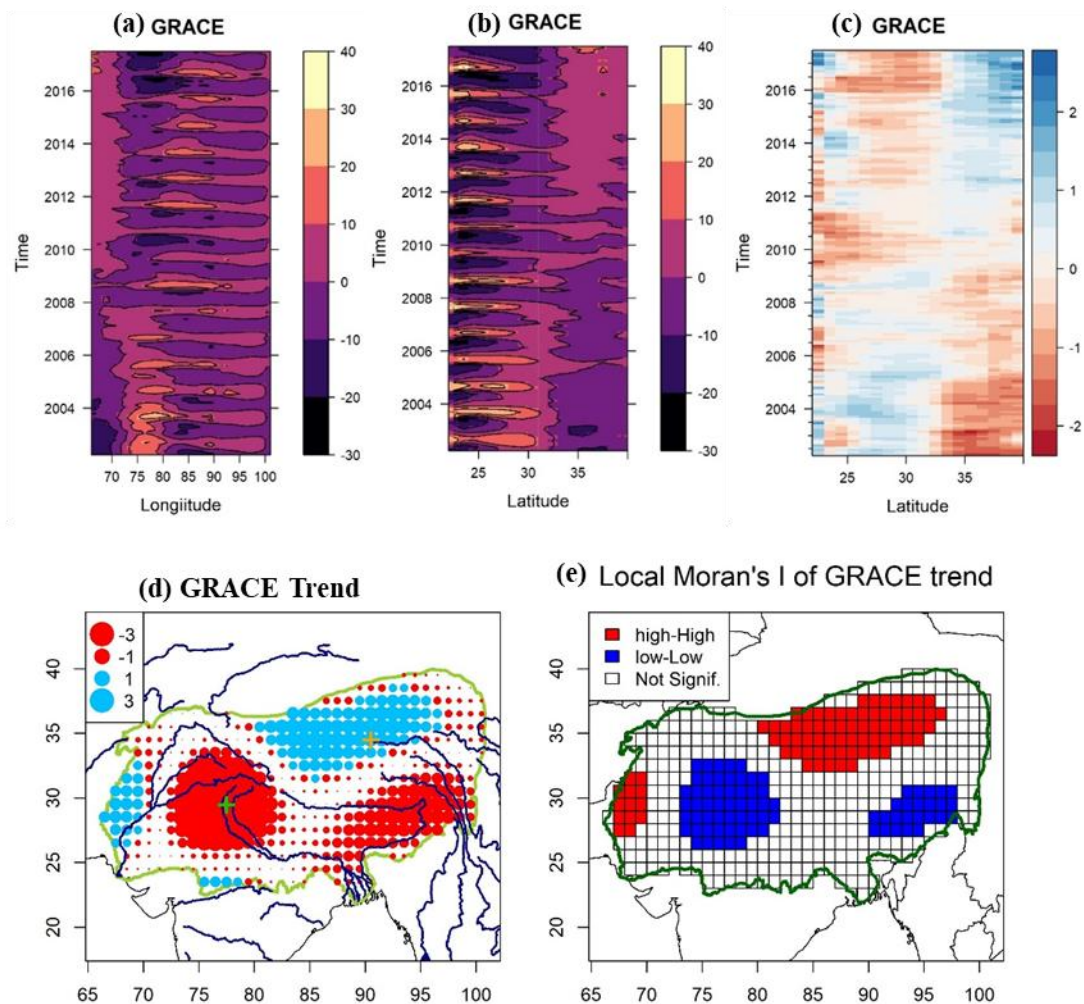
273 where $\mathbf{X}_i = \sqrt{K\lambda_i}\mathbf{u}_i\mathbf{v}_i^T$ ($i = 1, \dots, d$), are elementary matrices.

274 **3 Results**

275 3.1 The water shifting characteristics

276 Hovmöller diagrams (Hovmöller, 1949) were plotted to investigate the TWS
 277 spatiotemporal dynamic over the CIBA (66°E-101°E, 21°N-40°N) between 2002 and
 278 2017. According to the temporal variances of TWS along longitude and latitude,
 279 seasonal clusters were found along both longitude and latitude. Moreover, TWS
 280 showed an increasing trend over 80°E-90°E (the Chinese side) but a decreasing trend

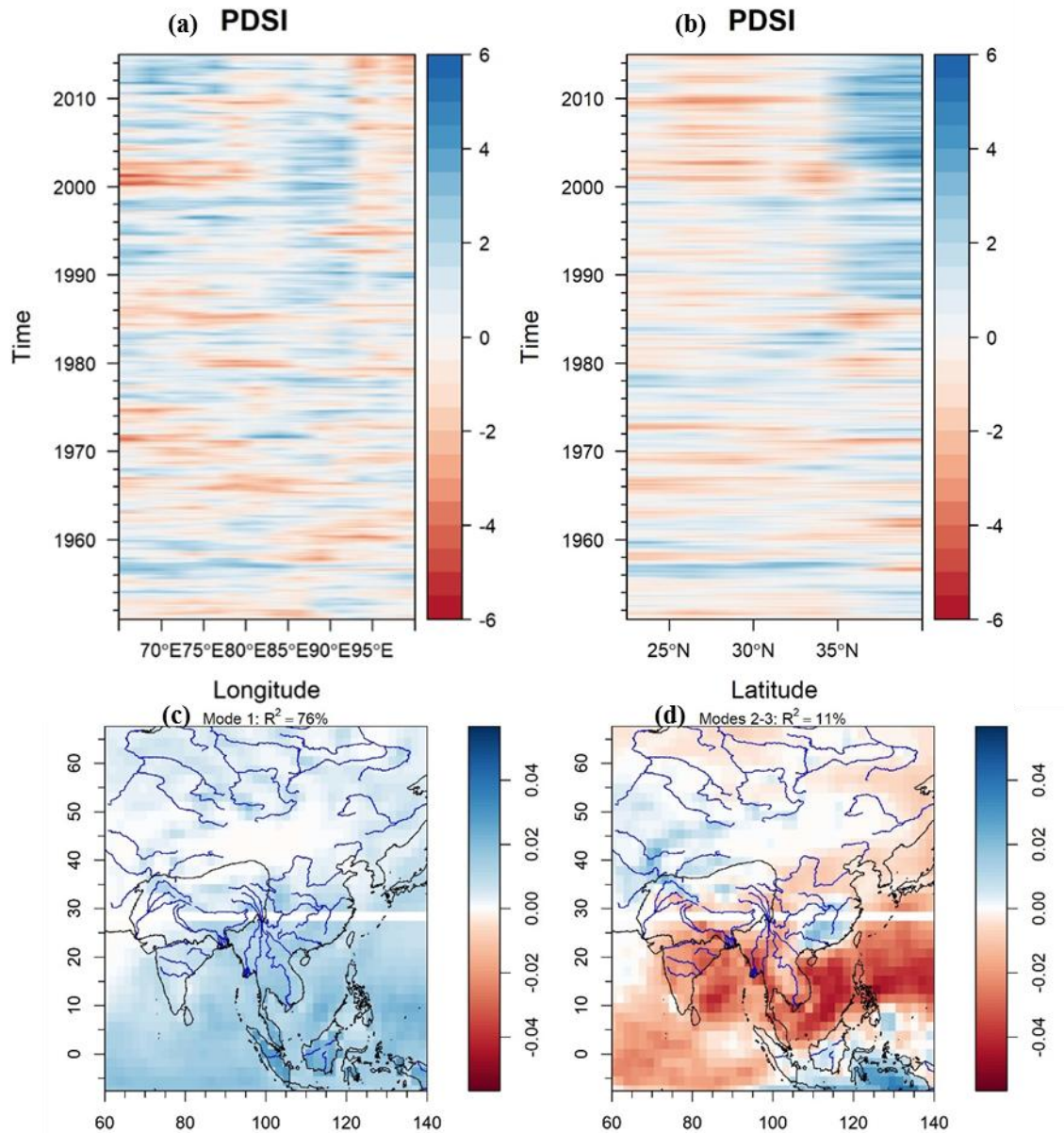
281 between 75°E and 80°E (the Indian side) (Figure 2a). In terms of latitude, the shift of
 282 TWS was even clearer. Figure 2b shows a decreasing trend between 28°N and 32°N
 283 and an increasing trend over 32°N-38°N. In order to get more apparent trend pattern,
 284 the Hovmöller diagram of seasonal TWS anomalies was shown in Figure 2c. It
 285 displays a distinctive increasing trend between 32°N and 38°N and a decreasing trend
 286 between 28°N and 32°N. The dividing line between increasing and decreasing trends
 287 was around the 32°N latitude.



288

289 **Figure 2.** Hovmöller diagrams of TWS (mm) along longitude (a) and latitude (b), and
290 the seasonal anomalies along latitude (c) over the CIBA region. Spatial trend
291 distribution of the TWS (d) and corresponding local Moran's I distribution (e) over
292 the CIBA. The blue and red circles represent the increasing and decreasing trend,
293 respectively. The orange and green crosses are the locations in western China and
294 northwestern India, respectively. The red and blue in (e) represent the high-high
295 hotspots and low-low hotspots respectively.

296 According to Figure 2a-c, the temporal TWS variances had clear spatial shifts
297 over the CIBA. Moreover, the spatial trend distribution of TWS and its LISA map
298 displayed three clusters (also called hot spots); two of them represented decreasing
299 trend, and one was increasing trend (Figure 2d-e). The increasing hot spot was located
300 at the region of 80°E-95°E, 32°N-37°N (i.e., western China), while decreasing hot
301 spots covered the regions of 72°E-82°E, 26°N-32°N (northwestern India) and
302 85°E-100°E, 25°N-31°N (Bangladesh, Figure 2d-e). The spatial trend pattern of TWS
303 was consistent with the Hovmöller diagrams of TWS (Figure 2a-c), indicating there
304 was a TWS shifting over the CIBA during 2002-2017.



305

306 **Figure 3.** Hovmöller diagrams of PDSI along longitude (a) and latitude (b) over the

307 GBB. The mode 1 (c) and combination of mode 2 and mode 3 (d) of TRMM

308 precipitation based on the SSA.

309 Apart from the TWS, the Hovmöller diagrams of TRMM derived-precipitation

310 and PDSI were shown in Figure 3. The Hovmöller diagrams of PDSI showed that

311 central QTP (87°E-92°E, 35°N-40°N) has been wetting (blue regions in the diagrams)

312 since the late 1980s (Figures 3a-b). After 2000, the northwestern India (26°N - 32°N)
313 has been drying (red regions in the diagram; Figure 3b). For precipitation, its seasonal
314 signals are very strong, which can mask the trend signals, leading to unclear
315 precipitation shifting pattern in the precipitation Hovmöller diagrams (not shown in
316 this paper). Therefore, we used SSA method to separate the seasonal and trend signals
317 (Figure 3c-d). The precipitation mode 1 represented the seasonal signal, which
318 accounts for 76% of the total variances. It explains 7 times of the variance explained
319 by the combination of mode 2 and mode 3 (hereafter called mode 2-3). The mode 2-3
320 accounts for 11% of the total precipitation variances, representing the secular trend
321 variances. It showed similar pattern with the spatial TWS trend distribution,
322 suggesting an increasing trend in western China and decreasing trend in other regions
323 of the GBB (Figure 3d).

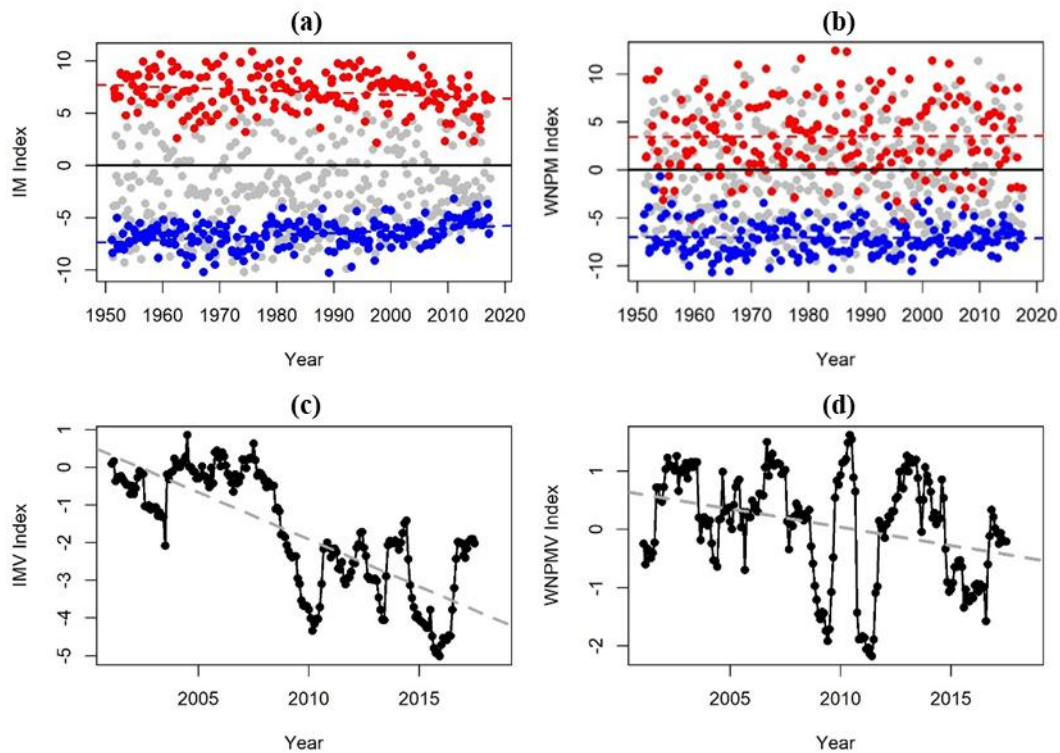
324 In addition, the potential evaporation distribution in Figure S1a showed a
325 drying-wetting trend pattern which is similar with that of the TWS. Changing TWS
326 over the IGBB during 2002-2017 can be directly caused by a more precipitation (and
327 less evaporation) trend over the central QTP and a precipitation decline (and
328 strengthened evaporation) over the IGBB (Figure 3d and Figure S1a). Similarly,
329 Figure S1b showed sharp declines of snow depths during 2002-2017 over the
330 northwest and the southeast corners of the QTP. These downward trends corresponded
331 well with the rising temperatures (Figure S1c). With the rising of the local
332 temperatures, a reducing snow depth trend (i.e., more snow melting) during
333 2002-2017 can be linked to increasing downstream surface waters such as the

334 expansion of lakes in the central QTP (Zhang et al., 2017). Therefore, for the QTP
335 region, the snow melting could be another important contributor to the TWS
336 variations.

337 In summary, the TWS water shifting pattern over the CIBA is wetting for the
338 western China and drying for the northwestern India. This shifting pattern could be
339 directly affected by precipitation, potential evaporation and snow melting, which are
340 mainly driven by the Asian monsoons modulated by regional temperature gradients.
341 Therefore, the impacts of Asian monsoons, including IM and WNPM, on the water
342 shifting since 2002 were investigated in next section.

343 3.2 Monsoon as a driving mechanism behind the TWS shifting

344 The summer IM index (for the months of JJA) had a decreasing trend, whereas
345 the winter IM index (for the months of DJF) had an increasing trend (Figure 4a).
346 However, for the monsoon intensity, the IM was weakening in both summer and
347 winter. Although it is less clear, the WNPM index showed similar weakening trend.
348 The weakening of the IM and WNPM could be the underlying drivers of water
349 shifting over the CIBA. To quantify this weakening effect, IM and WNPM variation
350 (hereafter called IMV and WNPMV) index were proposed based on the moving
351 standard deviation of the IM and WNPM index, showing the both IM and WNPM
352 strength were decreasing during 2002 and 2017 (Figure 4c-d). Particularly, the IMV
353 index fell abruptly since 2010.

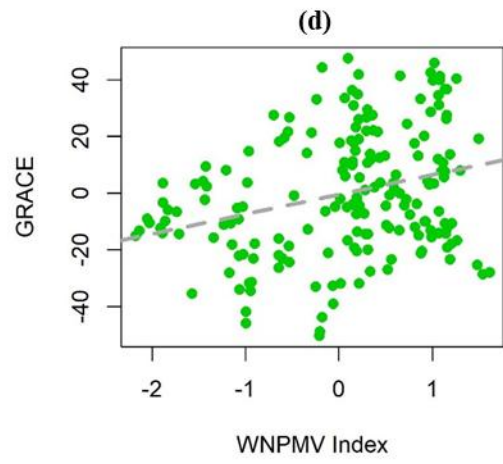
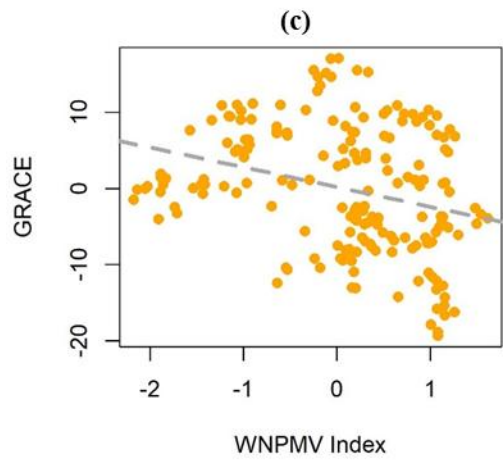
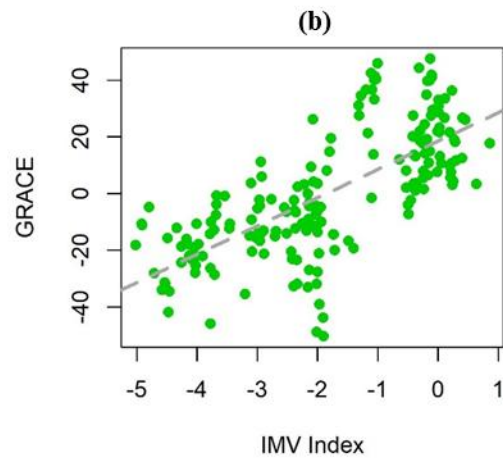
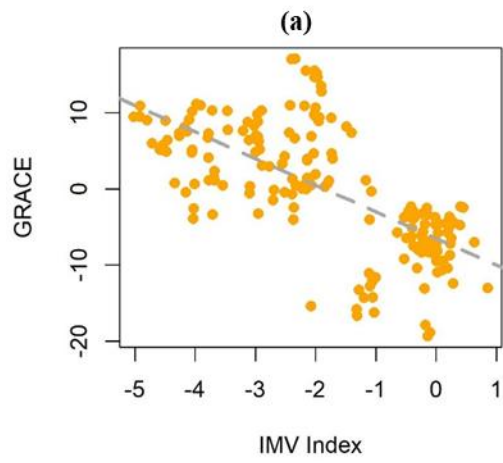


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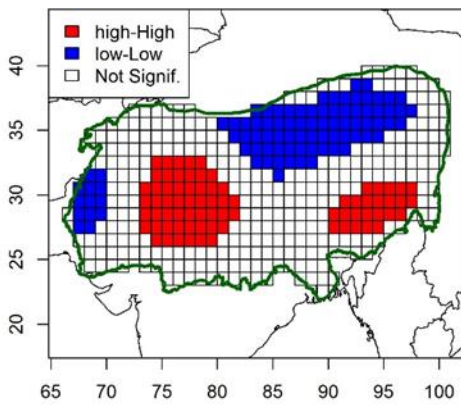
355 **Figure 4.** The monthly values of IM and WNPM indices during 1950-2017 (a-b) and
 356 the corresponding IMV and WNPMV indices during 2002-2017 (c-d). The red dots
 357 are the boreal summer (JJA) data and the blue dots are the winter (DJF) data in Figure
 358 4a and 4b.

359 For investigating the relationships between IM (and WNPM) and TWS over
 360 the CIBA, two TWS time series located in western China and northwestern India
 361 (orange and green cross respectively in Figure 2d) were extracted. There were no
 362 significant relationships between IM (and WNPM) and TWS in both the western
 363 China and northwestern India (Figure S2). However, a significant negative trend for
 364 the western China and a significant positive trend for the northwestern India between
 365 the IMV (and WNPMV) index and TWS were shown in Figure 5a-d. The results

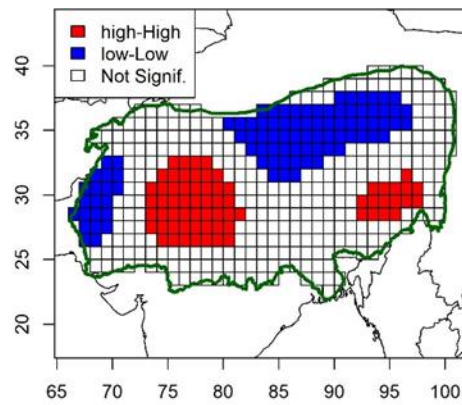
366 revealed that the weakening IM and WNPM could lead to an increasing TWS trend in
367 western China and a decreasing trend in northwestern India. Moreover, the LISA map
368 of the partial correlation of the IMV and TWS shared the similar pattern with that of
369 the WNPMV, showing significant negative and positive spatial clusters in western
370 China and northwestern India, respectively (Figure 5e-f), which was consistent with
371 the TWS trend patterns. Therefore, Figure 5a-f demonstrated that the TWS shifting
372 over the whole CIBA results from the weakening of the Asian monsoons. Additionally,
373 for the above-mentioned precipitation mode 2-3, representing the spatial precipitation
374 trend pattern, its temporal variation (hereafter called mode strength) was consistent
375 with the IMV and WNPMV step change (Figures S3), indicating that the precipitation
376 redistribution over the GBB was attributed to the IMV and WNPMV.



(e) Partial cor between GRACE and IMV



(f) Partial cor between GRACE and WNPMV



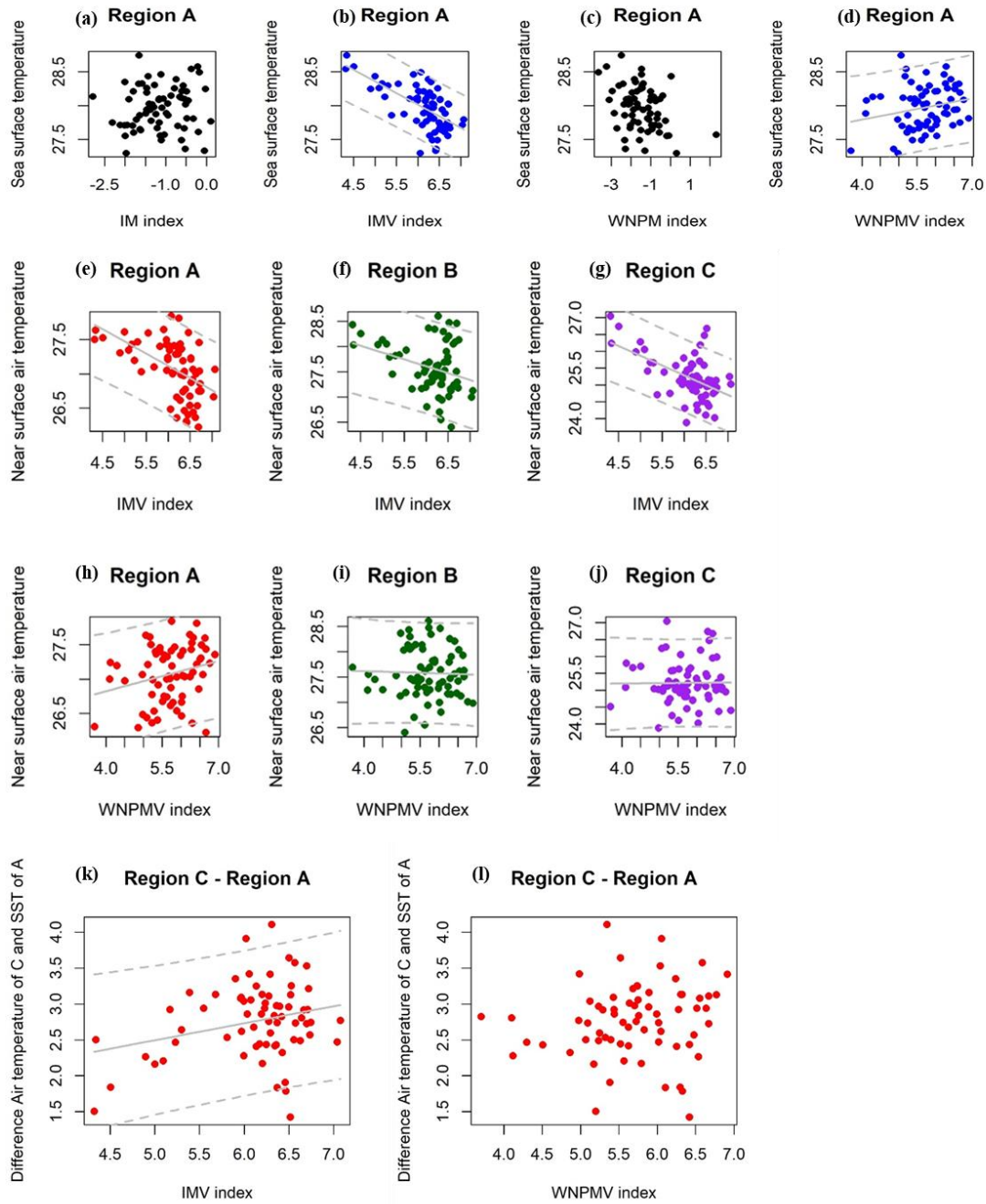
378 **Figure 5.** IMV and WNPMV against the TWS over the China (a, c) and India region
379 (b, d). The LISA map of partial correlation between TWS and IMV (e), and WNPMV
380 (f) over the CIBA.

381 3.3 Temperature drivers behind monsoons and TWS

382 The above results showed that the TWS shifting over the CIBA was caused by
383 the weakening of the IMV and WNPMV through modulating the precipitation
384 distribution. The IM and WNPM variability have been showed to be related to the sea
385 surface temperature (SST) (e.g., Annamalai et al., 2005; Weare, 1979; Xu et al., 2019),
386 the temperature of the QTP (e.g., Boos and Kuang, 2010; Zhao and Chen, 2001;
387 Zhisheng et al., 2015), and the land-ocean thermal difference (e.g., Roxy et al., 2015;
388 Tao et al., 2016; Yang et al., 2007). Therefore, to explore the relationship between
389 monsoons and surface temperatures, the average temperature over three regions
390 located in the Indian Ocean (hereafter called Region A), the Ganges (hereafter called
391 Region B) and the Brahmaputra (hereafter called Region C) were extracted (Figure
392 S4).

393 The Figure 6 showed the relationships between mean annual temperature in
394 different regions and monsoon indices for 70 years. Both the IM and WNPM indices
395 were not related to the mean SST of Region A (Figure 6a and 6c), while the IMV and
396 WNPMV fitted well with negative and positive relationship for the SST, respectively
397 (Figure 6b and 6d). Moreover, negative relationships between the IMV and the near
398 surface air temperature (NSAT) were found in all regions (Figure 6e-g). For the

399 WNPMV, it showed a positive relation with the NSAT at Region A, but negatively
400 correlated with the NASTs at Region B and Region C (Figure 6h-j). These outcomes
401 showed that the local and ocean temperature can modulate the monsoon variations.
402 The negative relationships between temperatures and the IMV at three regions
403 revealed that rising regional air temperatures and SST caused by increasing global
404 temperatures may be the driver of the IM weakening. In addition, the IMV had a
405 positively weak but statistically significant relationship with the thermal difference
406 between Region A and Region C, while the WNPMV showed no significant
407 relationship with the land-ocean thermal difference (Figures 6k-l), because it was
408 more likely related to the thermal difference between the Asian land surface and the
409 tropical Pacific Ocean based on its definition (Li and Hsu, 2018). Therefore, the
410 land-Indian Ocean thermal difference may play a weak role for changing monsoons
411 and thus the TWS spatial patterns.



412

413 **Figure 6.** IM, IMV, WNPM and WNPMV index against the SST in Region A (a-d);

414 IMV and WNPMV index against the NSAT in Region A, Region B and Region C (e-j);

415 IMV and WNPMV index against the air temperature difference between Region A and

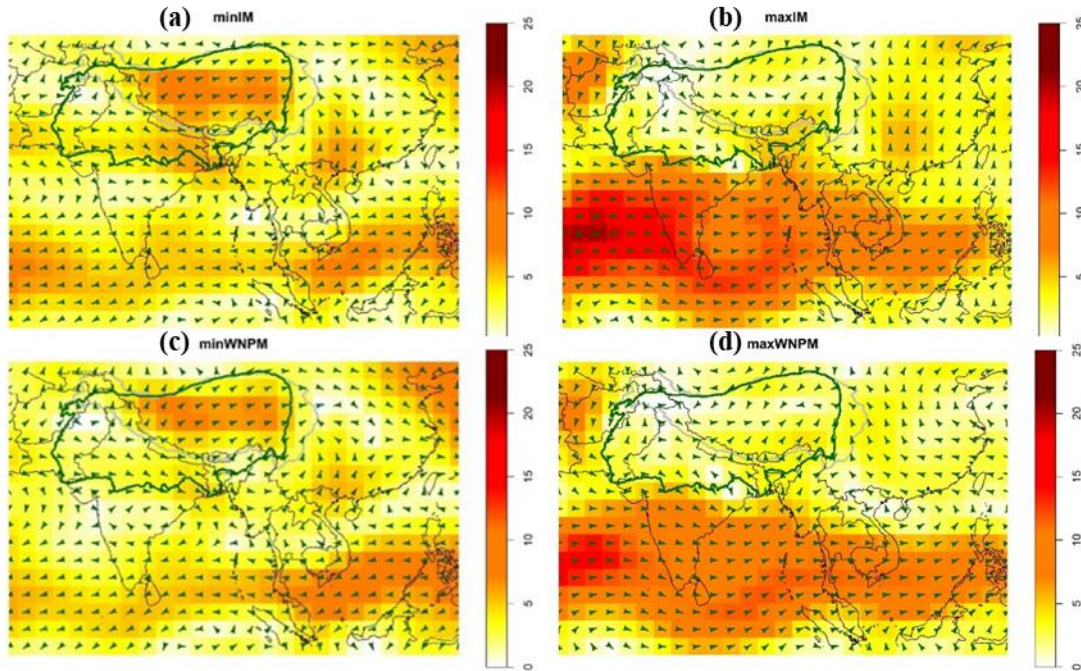
416 Region C (k-l).

417 **4 Discussion**

418 The TWS trend pattern and the Hovmöller diagrams clearly showed the spatial
419 clusters over the CIBA. There were (1) a significant decreasing cluster over the upper
420 Indus and Ganges (i.e., northwestern India), (2) an increasing cluster over the central
421 QTP (i.e., western China) and (3) a decreasing cluster over the southeastern
422 Brahmaputra basin (i.e., Bangladesh). In addition to decreasing precipitation and
423 increasing potential evaporation, the TWS decline in the IGBB was also probably
424 attributed to the over-exploitation of underground water for water supply in
425 agriculture and industrial sectors in northern India and Bangladesh (Rodell et al., 2009;
426 Shamsudduha et al., 2012). Given the TWS decline and population increase, the
427 IGBB region has now been facing severe water scarcity (Babel and Wahid, 2009), and
428 the situation will become more serious if no measure is taken.

429 Apart from the anthropogenic effect, the monsoon variability is a main natural
430 driver to the TWS shifting over the CIBA. Based on the monsoon variation analysis,
431 the weakening of the IMV and WNPMV were significant contributors to the
432 increasing TWS over the western China and the decreasing TWS over the
433 northwestern India. During winter (Figures 7a and 7c), less strong dry monsoon winds
434 come from the Himalaya over the Qinghai-Tibet Plateau; during summer (Figures 7b
435 and 7d), weak monsoons would bring less moist winds from the Arabian Sea to India.
436 Weaker and less moist winds would lead to drying windward side and wetting leeward

437 side of the Himalaya, and thus an increasing TWS over the western China and a
438 decreasing TWS over the northwestern India.

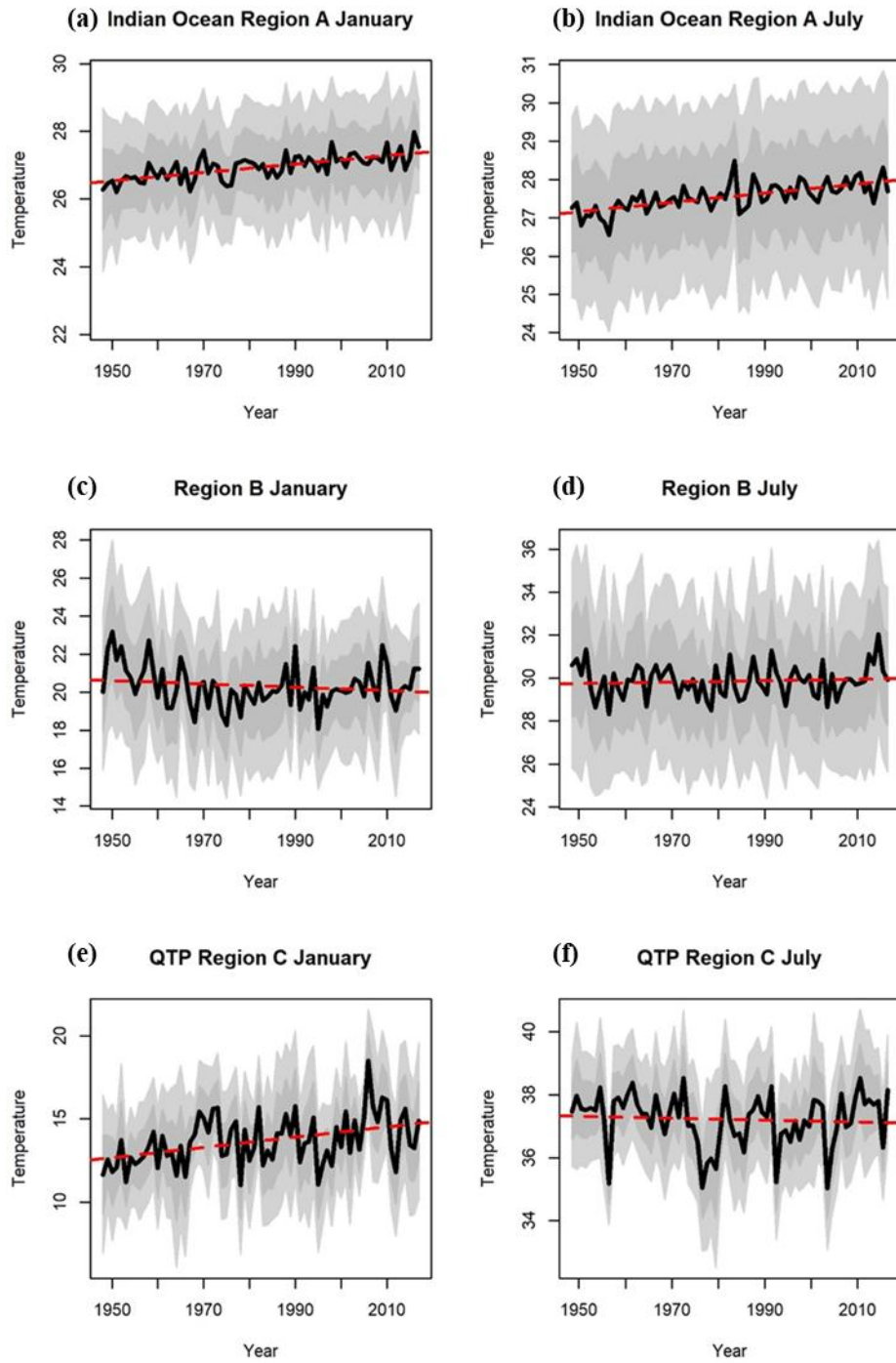


439

440 **Figure 7.** The average wind field of the lowest and highest 10% IM index (a-b),
441 representing the winter monsoons and summer monsoons, respectively. (c-d) are same
442 as (a-b) but for the WNPM.

443 According to the Figures 8a-b, the Indian Ocean (Region A) had a clear
444 temperature increasing in both summer and winter. This temperature change led to the
445 weakening of the IM, based on the negative relationship between IMV and SST in
446 Region A (Figure 6b). The temperature over the Region B showed no obvious trend in
447 both summer and winter (Figures 8c-d). The QTP (Region C) showed an increasing
448 temperature trend in winter (Figure 8e), but no obvious trend in summer (Figure 8f).
449 The increasing trends of temperature over the Indian Ocean were larger than that over

450 the QTP in both winter and summer, indicating that the thermal difference between
451 the Indian Ocean and QTP was decreasing, leading to the decrease in the IM intensity
452 based on the positive relationship between IMV and temperature difference shown in
453 the Figure 6k. For the WNPMV, the increasing temperature over the Region A
454 indicated the strengthening of the WNPMV based on the positive relationship
455 between WNPMV and SST over Region A (Figure 6d). However, this result is not
456 consistent with the WNPMV weakening. This inconsistency can be explained by the
457 complex interactions between the Indian Ocean and the Pacific Ocean, and the
458 WNPM is less important for the CIBA, compared to the IM (Luo et al., 2010; 2012).



459

460 **Figure 8.** The average temperature variation over time in winter (January) and

461 summer (July) over the Region A (a-b), Region B (c-d) and Region C (e-f).

462 **5 Conclusion**

463 In this study, we use the Hovmöller diagrams, the spatial TWS trend patterns
464 and their LISA maps to show that the TWS over the western China part was
465 increasing and the TWS over the northwestern India part was decreasing. The
466 precipitation and potential evaporation showed similar drying and wetting patterns
467 with the TWS, and snow melting due to the rising temperature can be an important
468 contributor to the TWS increase over western China (i.e., central QTP). The water
469 shifting pattern between 2002 and 2017 over the CIBA were controlled by the
470 changing Asian monsoon (i.e., IM and WNPM) and local temperature through the
471 modulation of precipitation, evaporation and snow melting.

472 The intensity of both IM and WNPM showed a gentle decreasing trend during
473 1950-2017. Furthermore, in order to emphasize the monsoon variation, IMV and
474 WNPMV were calculated based on the traditional monsoon indices, revealing that the
475 monsoon decreased dramatically during 2002-2017. In addition, the TWS over the
476 drying region (i.e., northwestern India) was positively correlated with IMV (and
477 WNPM), whereas the relationship between the TWS over the wetting zone (i.e.,
478 western China) and IMV (and WNPMV) was negative. This result suggested that the
479 weakening of the IM led to the decreasing and increasing trends of TWS over two
480 different regions of the CIBA. Moreover, similar clusters on the LISA maps further
481 show that the weakening monsoons caused the TWS redistribution over the CIBA.

482 Finally, the ocean and continental temperature difference changes modulated
483 the IM and WNPM variability, and they led to the TWS shifting over the CIBA. The
484 temperatures over the QTP, the Ganges, and the Indian Ocean were negatively
485 correlated with the IMV, indicating that increasing local temperatures weakened the
486 IM, and thus affecting the TWS shifting. Meanwhile, the decrease in the thermal
487 difference between the QTP and the Indian Ocean can also explain the weakening of
488 the IM because of their positive relationship.

489 In this study, we looked at monsoon roles for changing TWS. Although the
490 Glacial Isostatic Adjustment (GIA) were applied to the TWS data, the glacier effect
491 can be important for explaining the observed TWS shifts. The observed drying center
492 at the headwater of the Ganges can be related to the Gangotri glacier which is one of
493 the largest glaciers in the Himalayas. The Gangotri glacier has been retreating at a
494 significant rate between 22 and 27 m/year (Bhambri et al., 2011; Jain, 2008). The
495 glacier retreat could be another explanation of decreasing TWS over the Ganges due
496 to the temperature changes.

497 In summary, our findings have linked spatial water shifting over the CIBA to
498 monsoon variations and changing local or even global temperature gradients. The
499 main limitation of the study is whether the detected TWS shifting will last after 2017.
500 For future studies, it will be worthwhile to project future TWS distributions using the
501 temperature gradients derived from climate model outputs based on different
502 Representative Concentration Pathways (RCPs). Then, these projected water

503 conditions can help decision-makers to propose water management designs, including
504 (1) establishing water consumption quotas for regions having declining TWS and (2)
505 setting up flood control measures for places having increasing TWS. Therefore, the
506 dynamic relationships between temperature gradient, TWS and monsoons in this
507 study is not only building blocks for exploring the mechanisms of shifting
508 hydroclimatic systems, but also providing new insights for future water management
509 designs to the region.

510 **Acknowledgments**

511 This research was funded by the Hong Kong Baptist University Faculty research Fund
512 (FRG1/1617/005, FRG2/1617/082, FRG2/1516/085), the National Natural Science
513 Foundation of China (NSFC) (Grant No. 41974003, 41674007), and The Scientific and
514 Technological Research Council of Turkey (TUBITAK) 2232 grant (118C329). This
515 research was conducted using the resources of the High Performance Cluster
516 Computing Centre, Hong Kong Baptist University, which receives funding from
517 Research Grant Council, University Grant Committee of the HKSAR and Hong Kong
518 Baptist University. The datasets used in this study are publicly available, and the
519 corresponding URLs are provided in the section 2.

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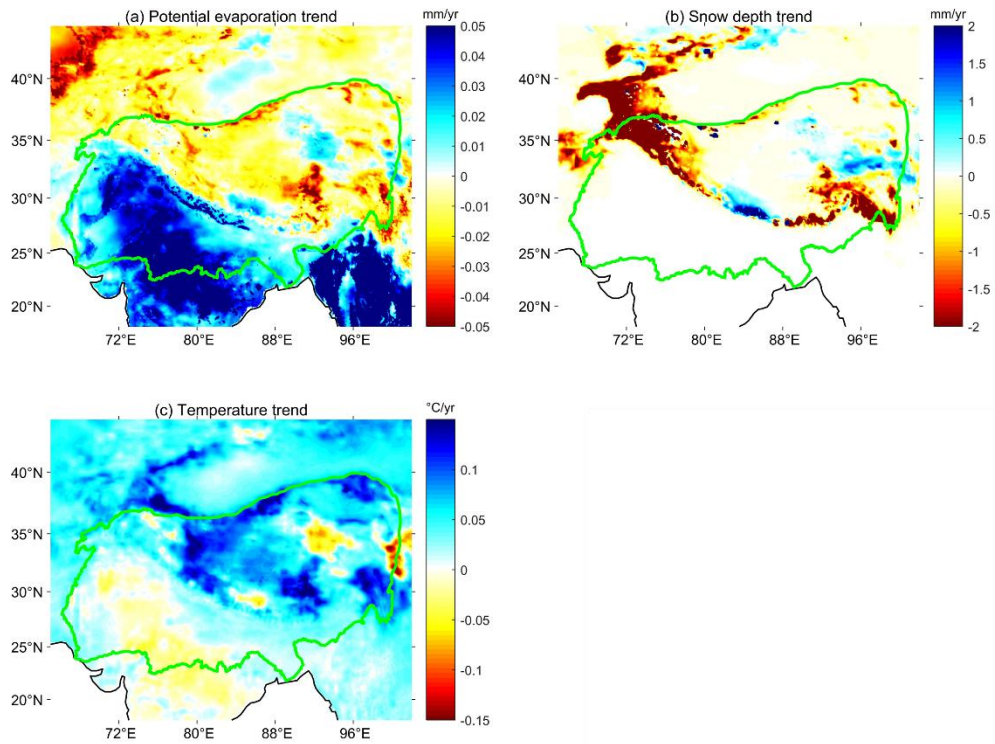
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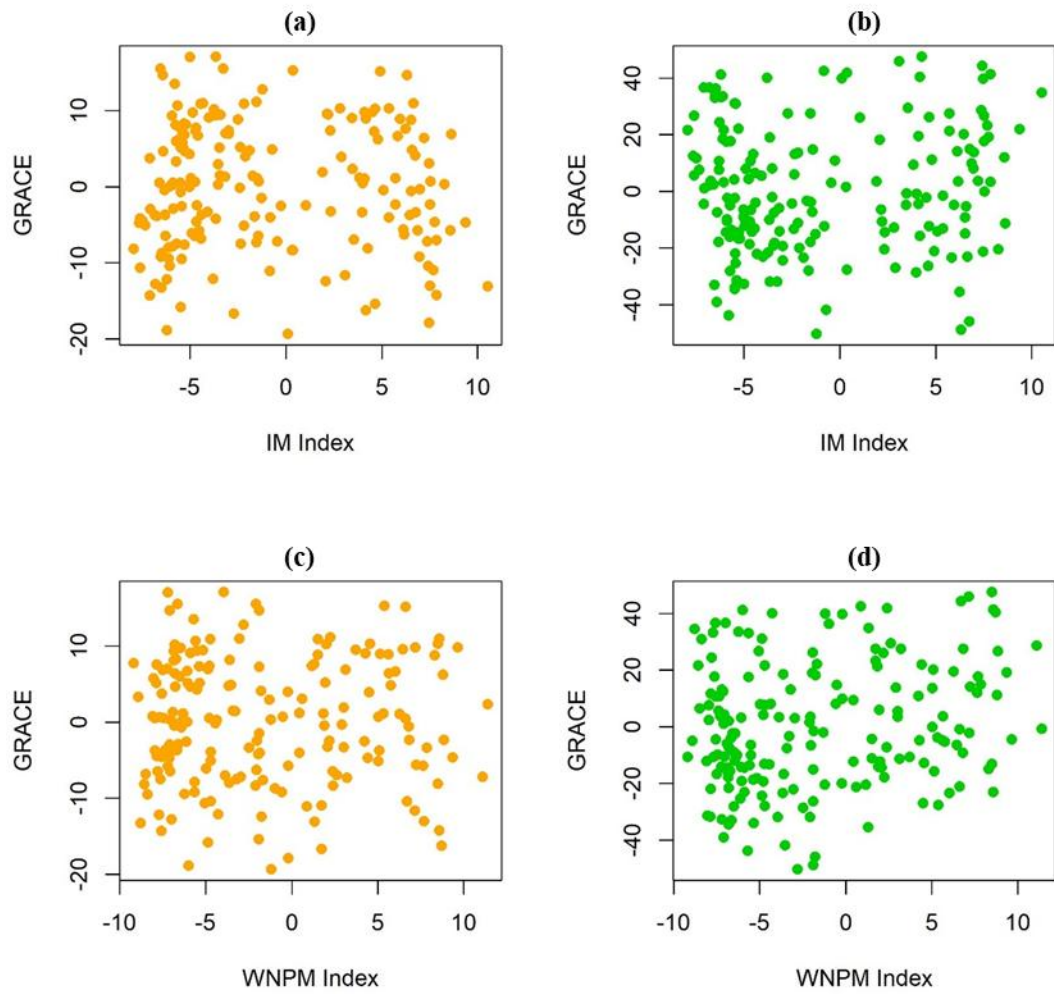
720 **Appendix**



721

722 **Figure S1.** The potential evaporation (a), snow depth (b) and temperature trend (c) pattern over

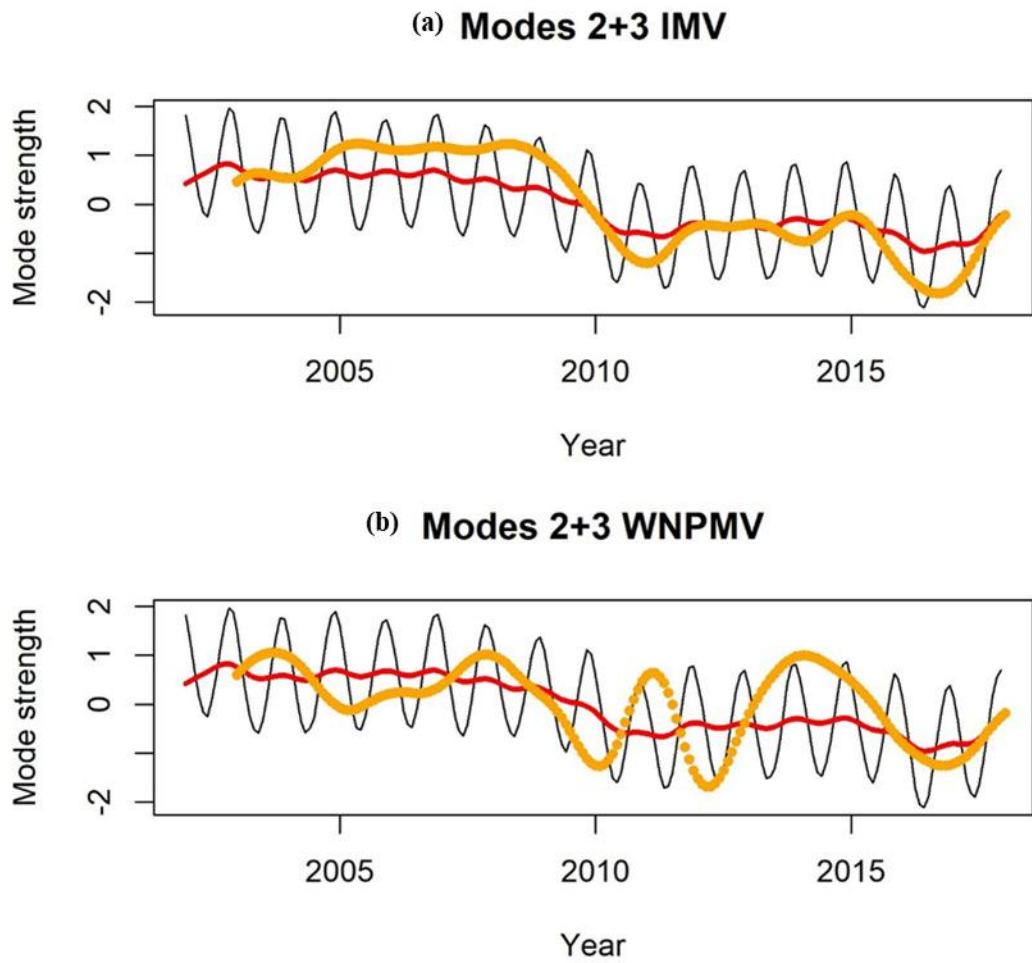
723 the CIBA.



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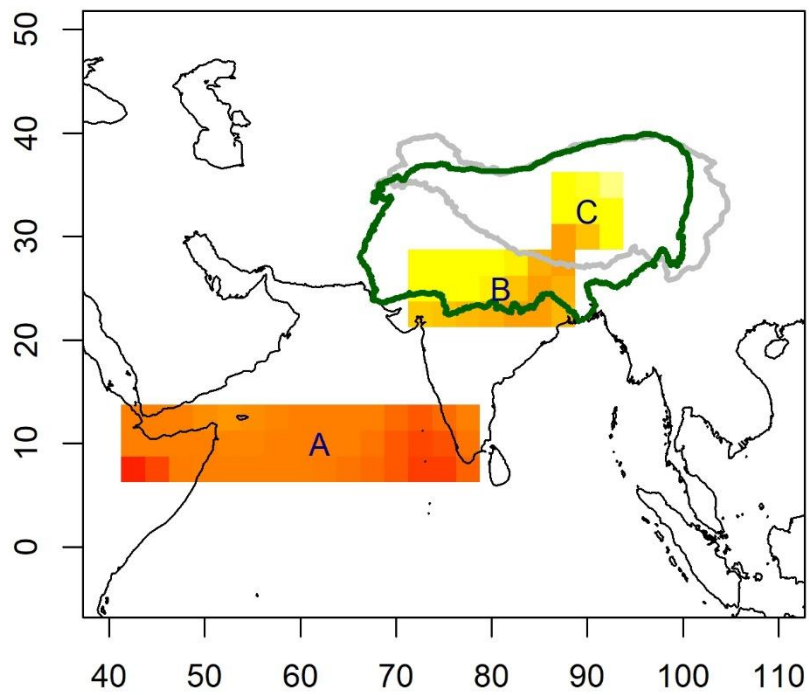
725 **Figure S2.** The IM and WNPM index against the TWS over the China (a, c) and India

726 region (b, d) of CIBA.



727

728 **Figure S3.** The mode strength of precipitation mode 2-3 (red) against the IMV (a) and
 729 WNPM step change (orange) (b).



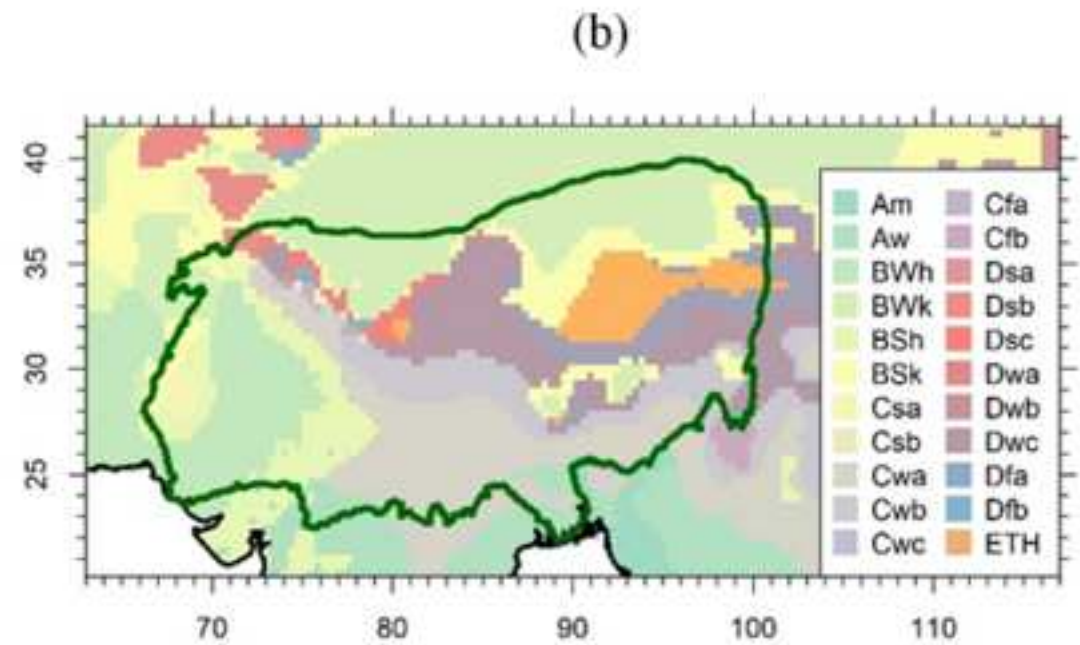
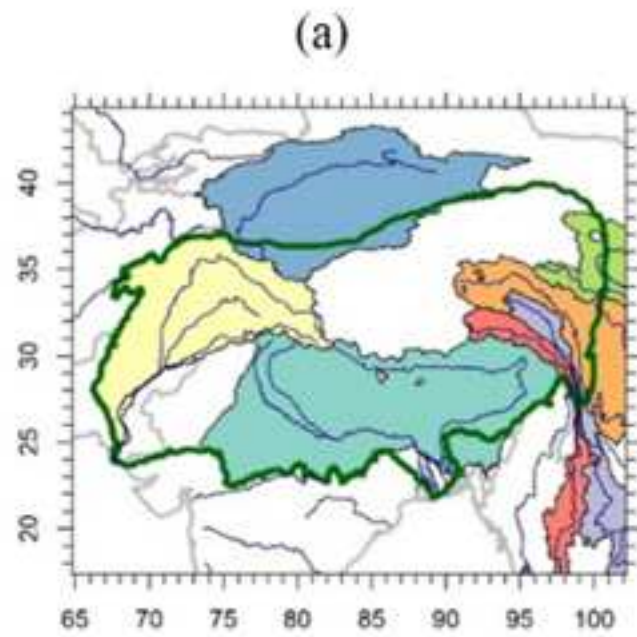
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731 **Figure S4.** The selected temperature locations.

732

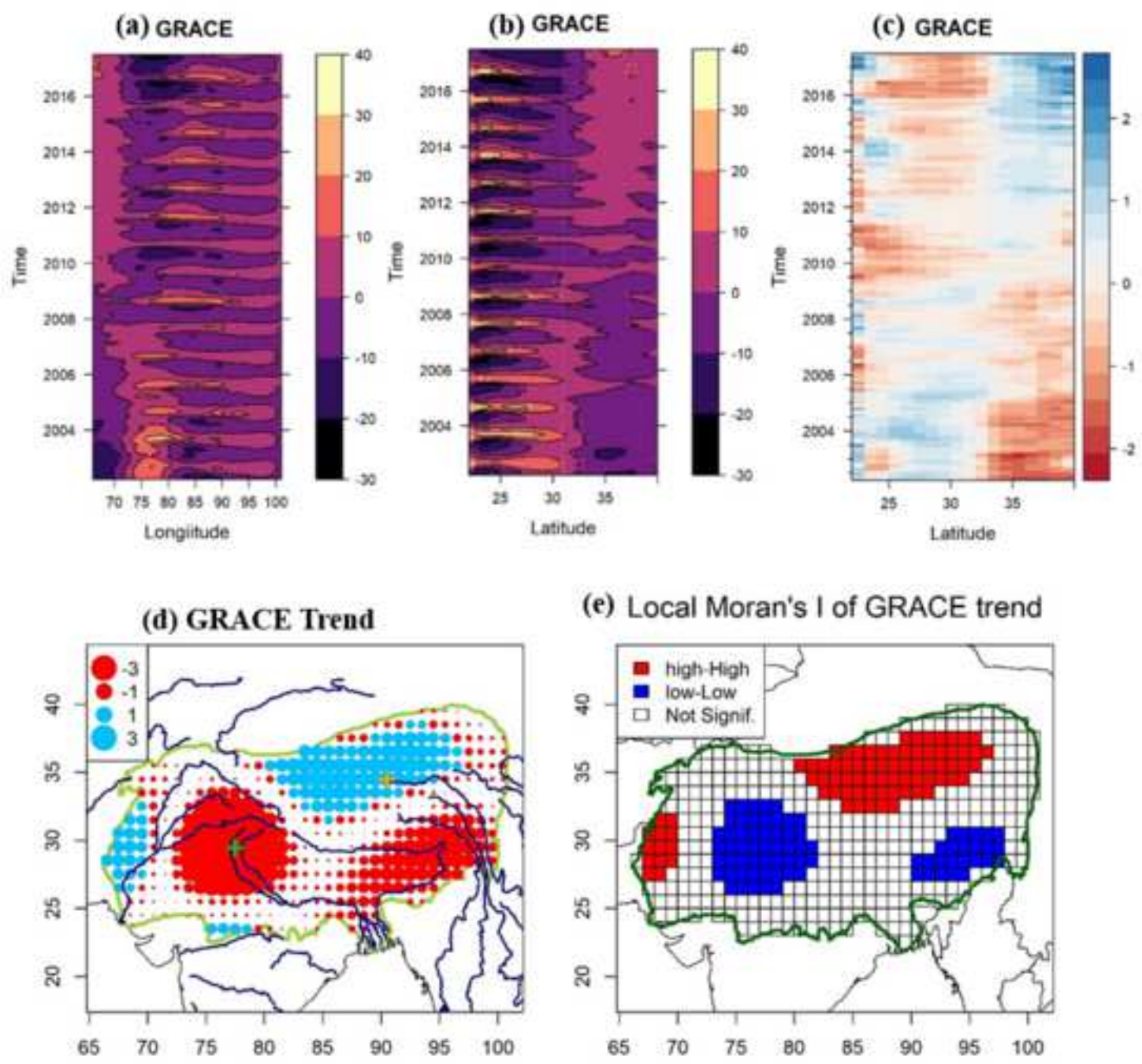
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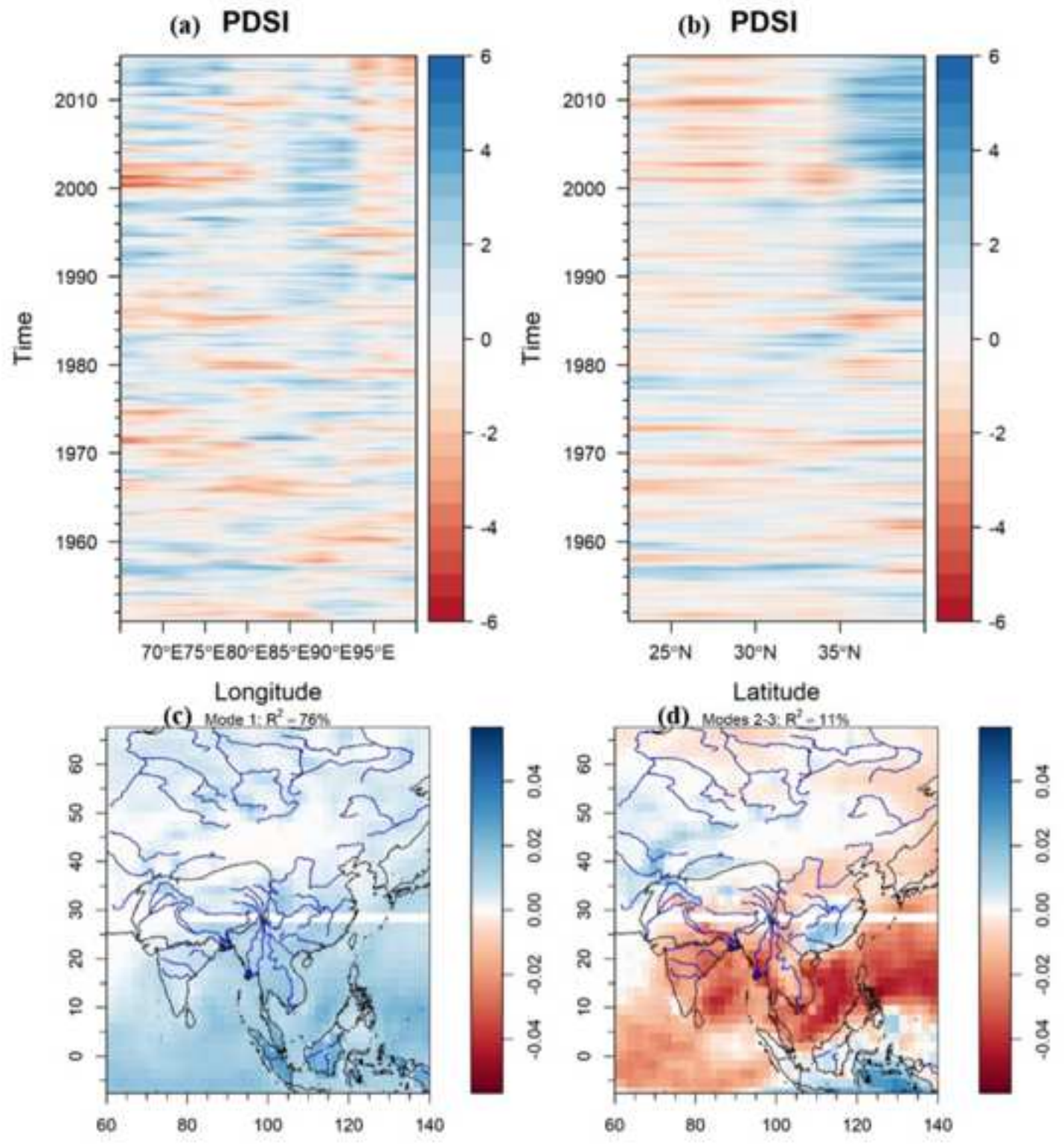
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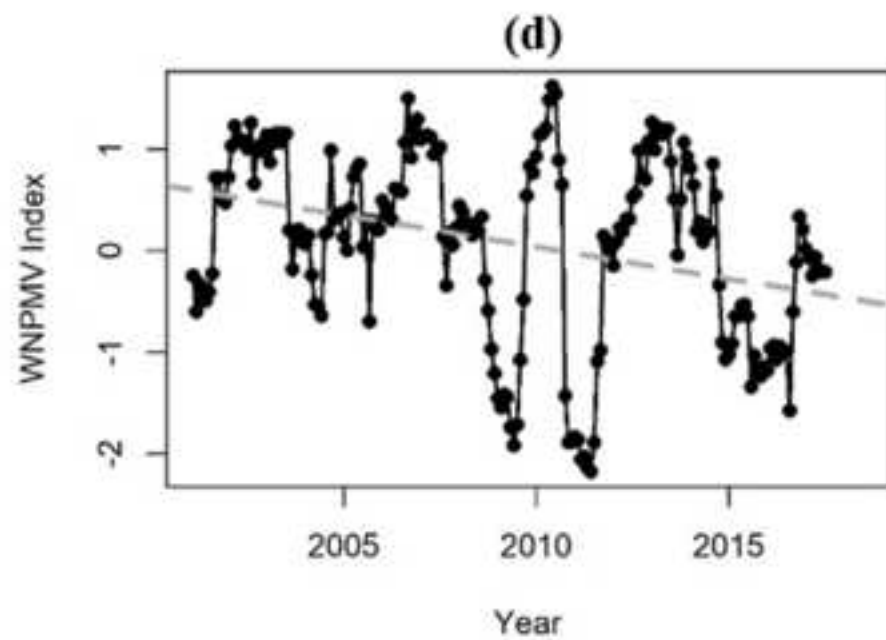
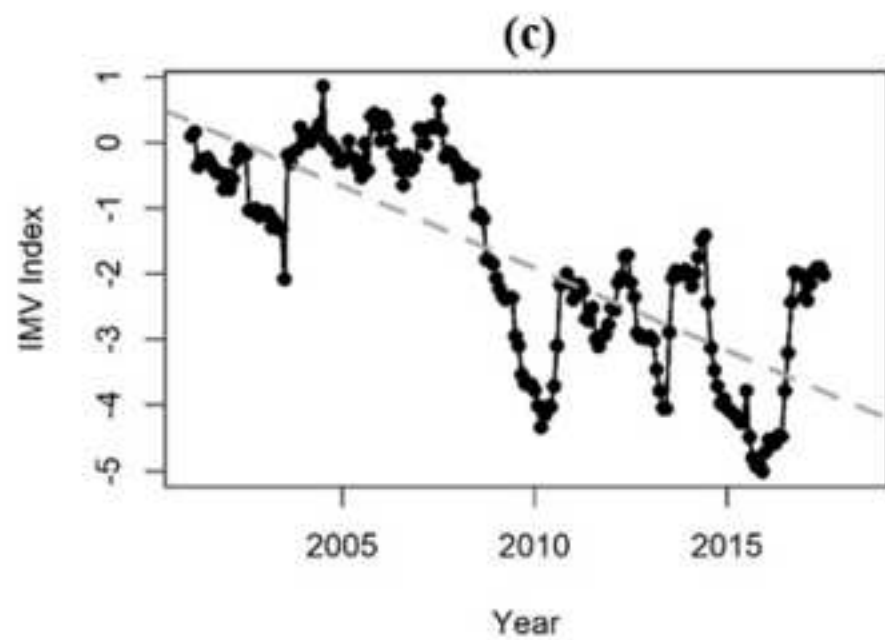
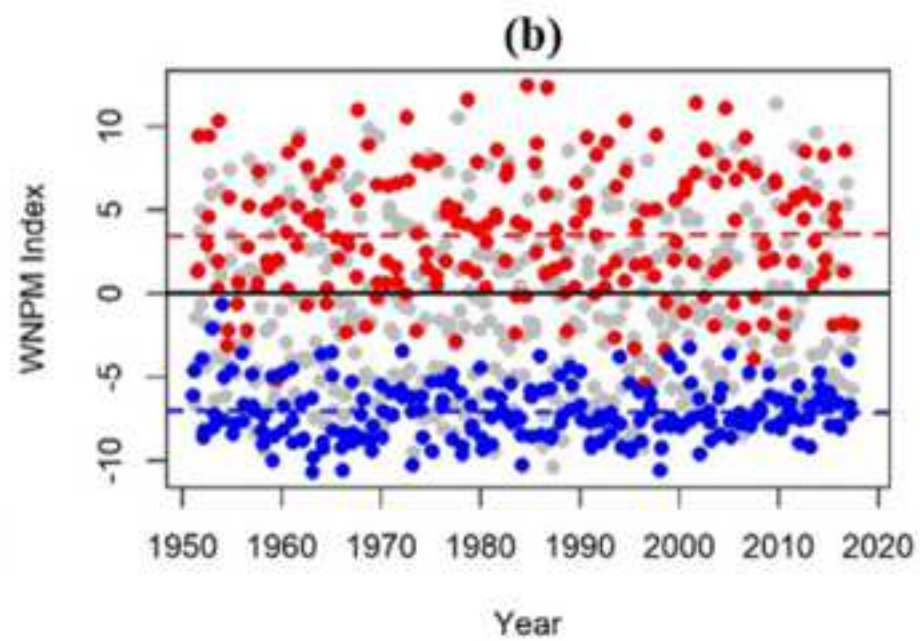
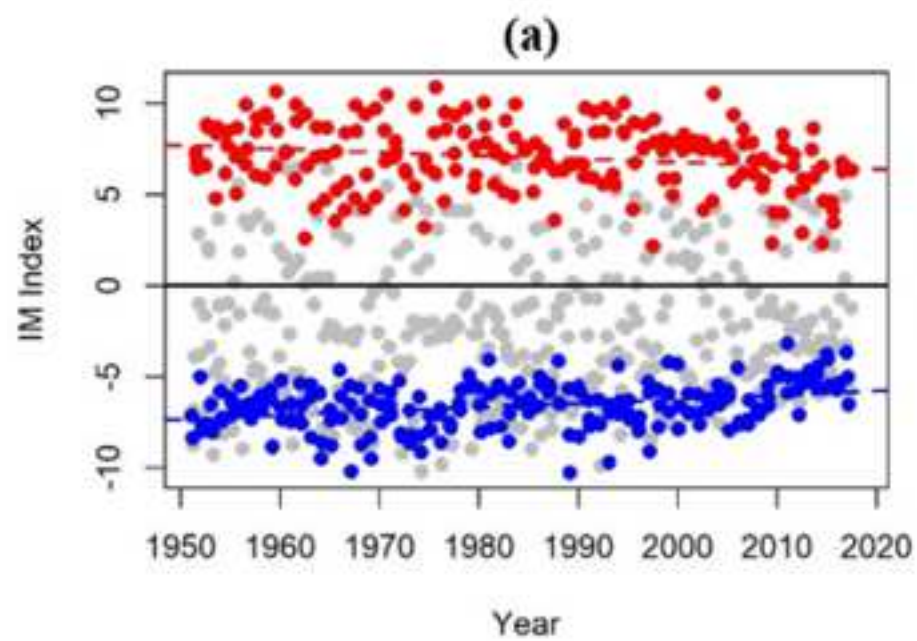
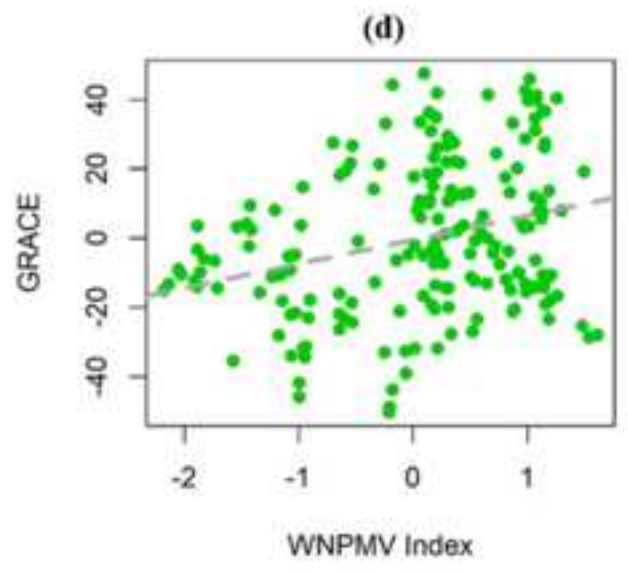
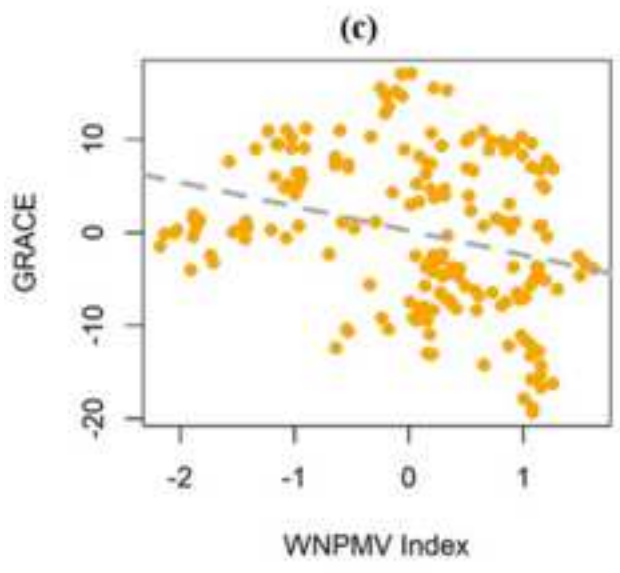
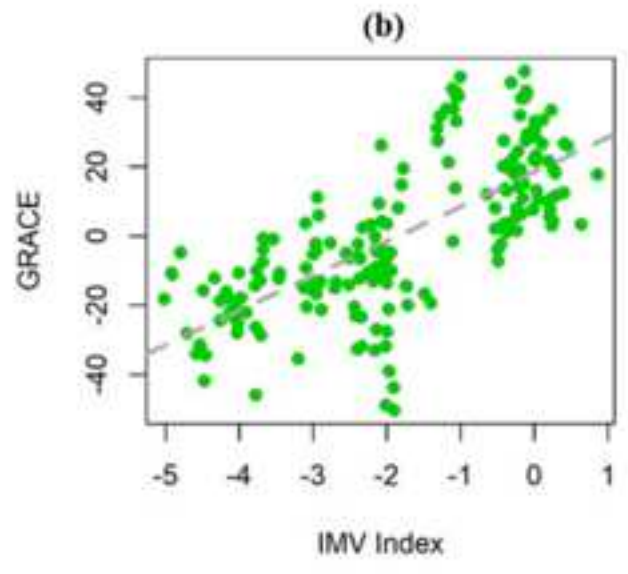
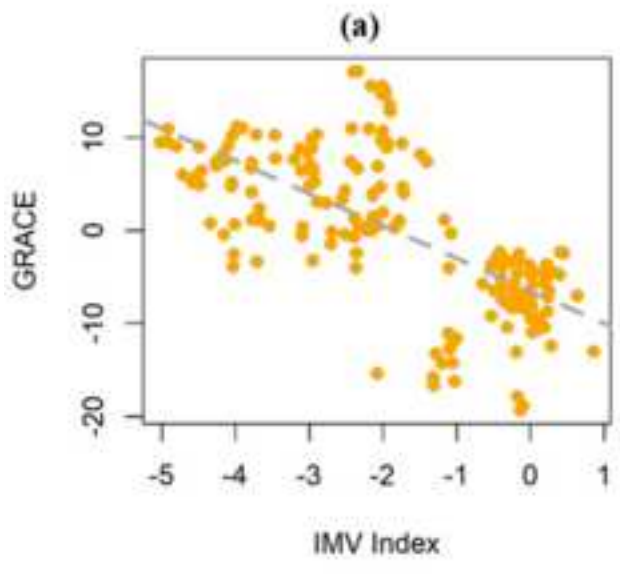
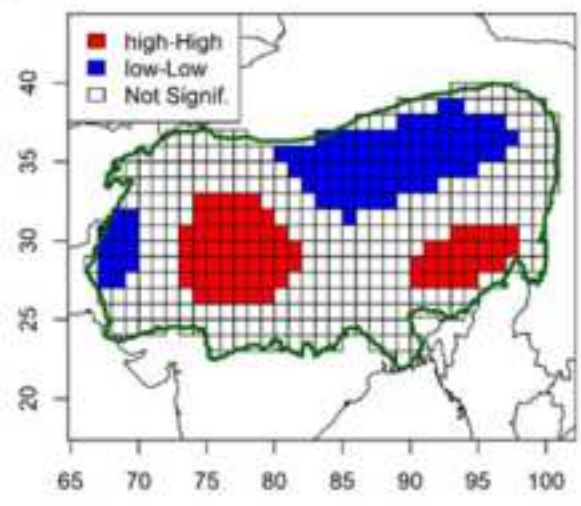


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(e) Partial cor between GRACE and IMV



(f) Partial cor between GRACE and WNPMV

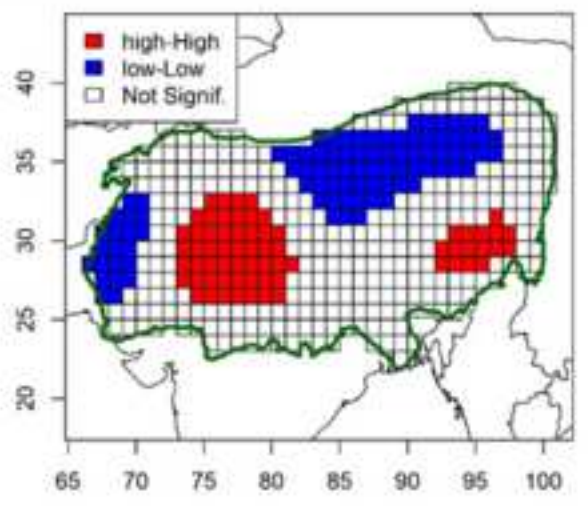
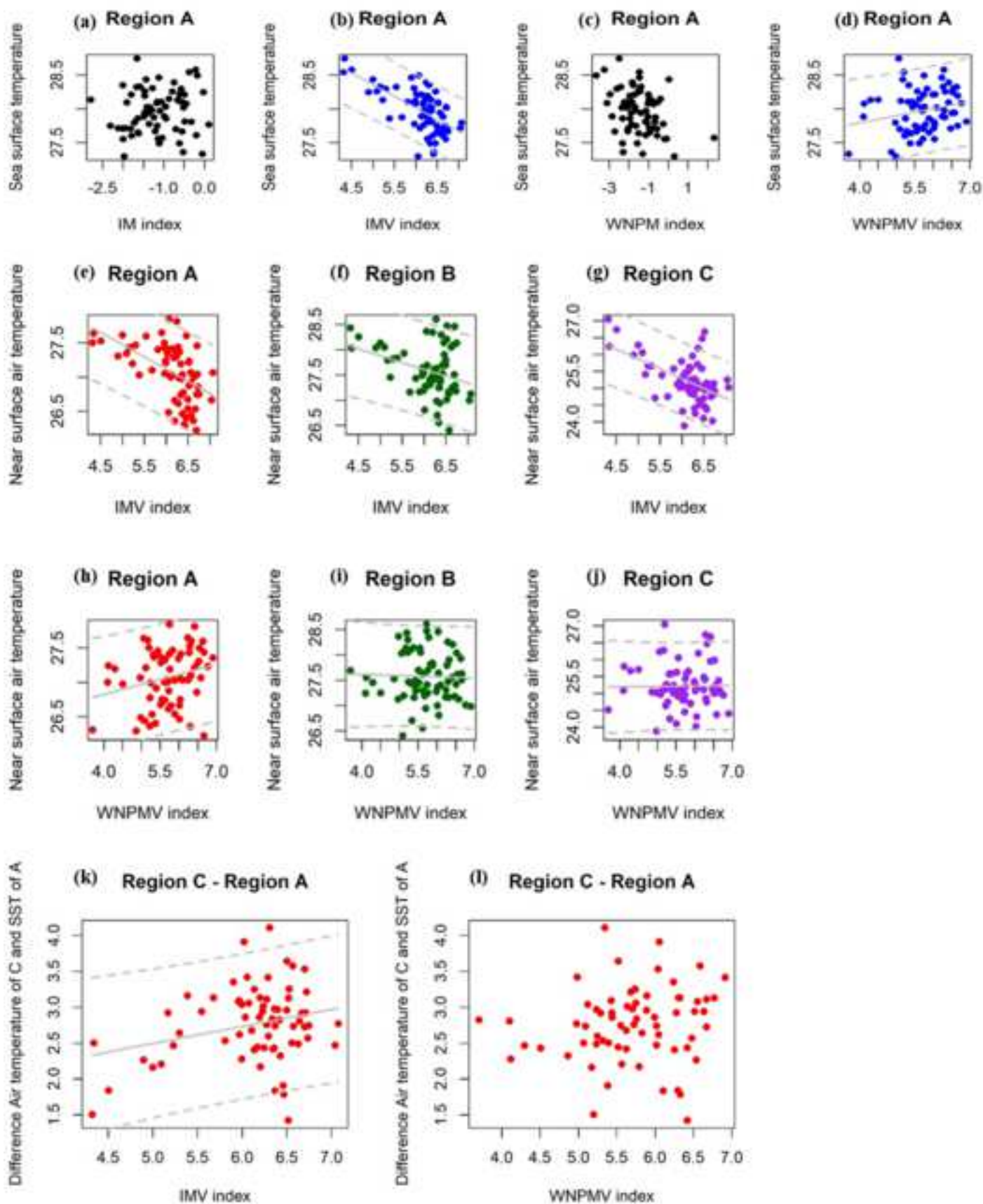
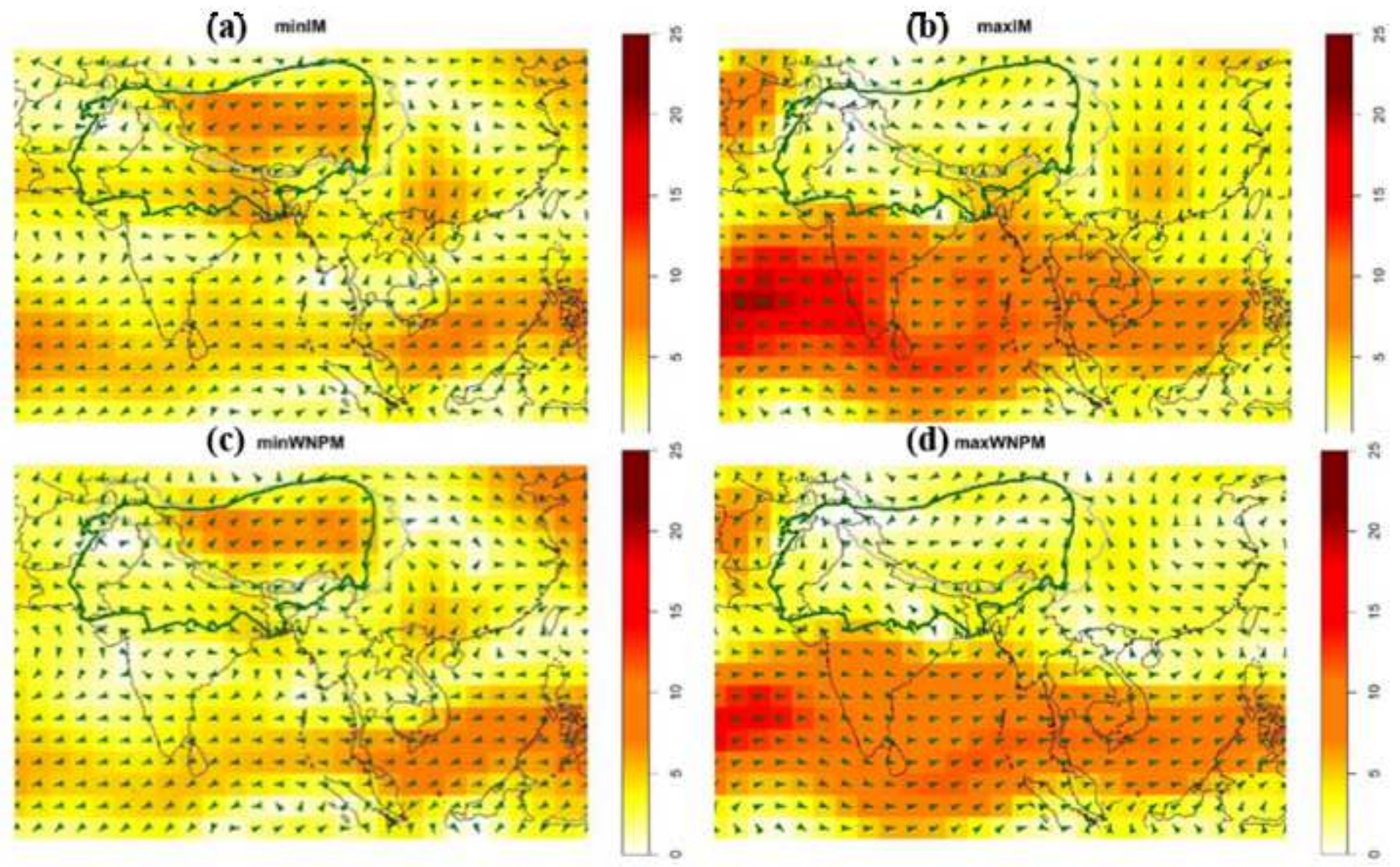


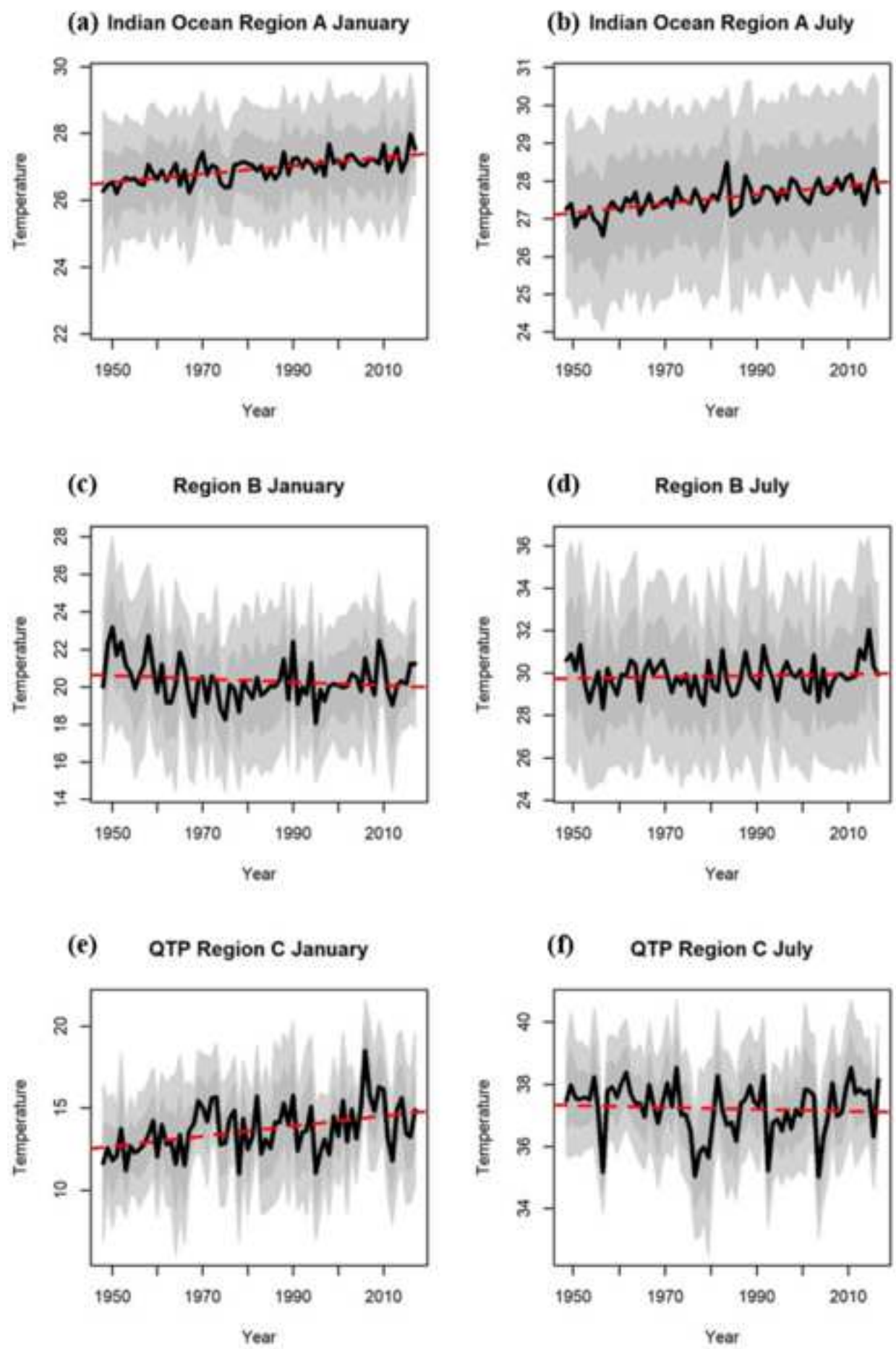
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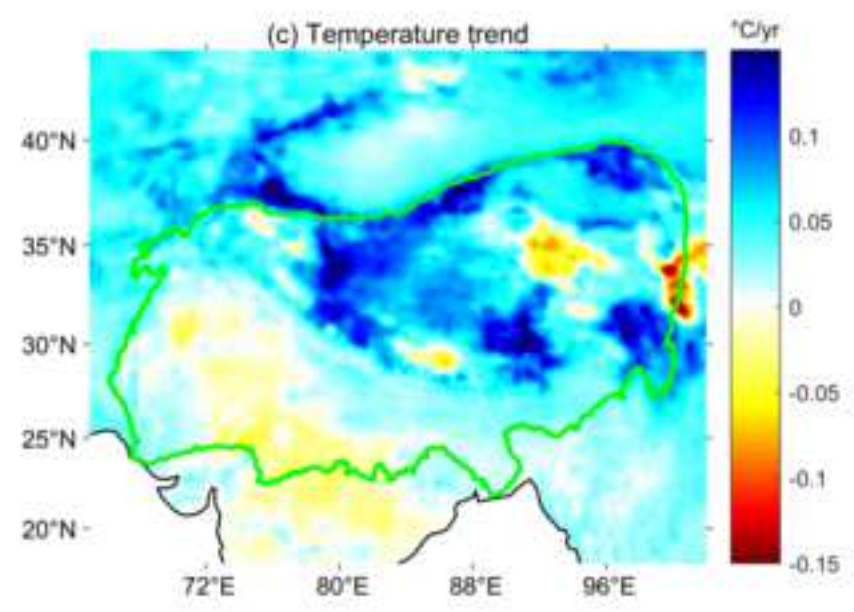
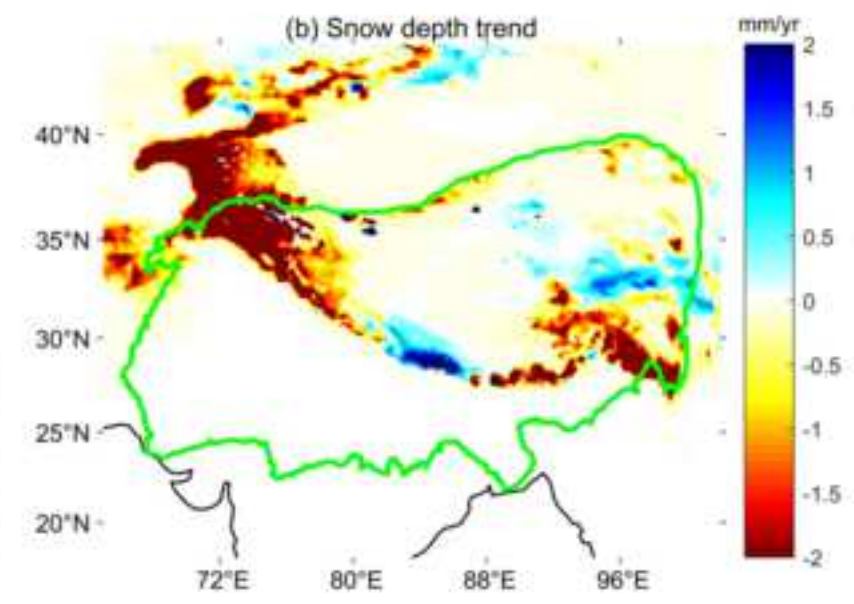
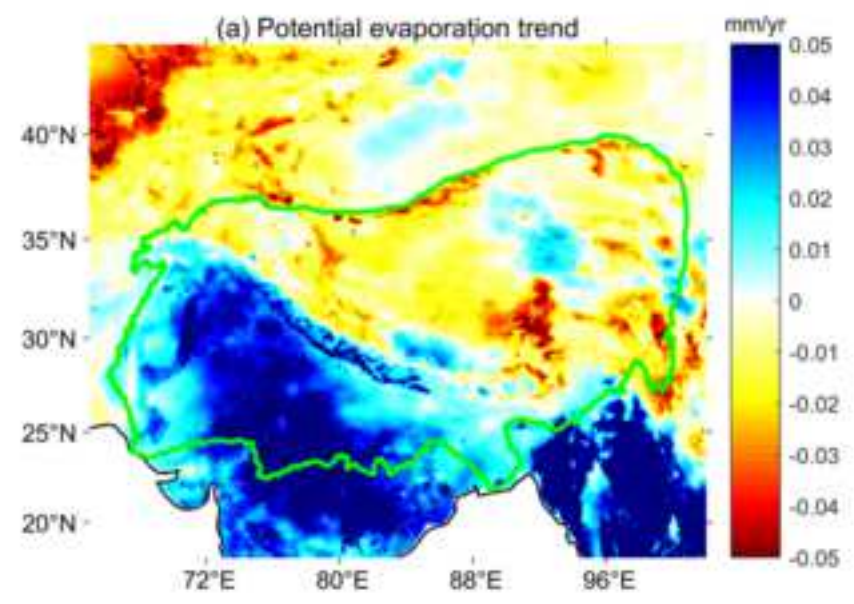
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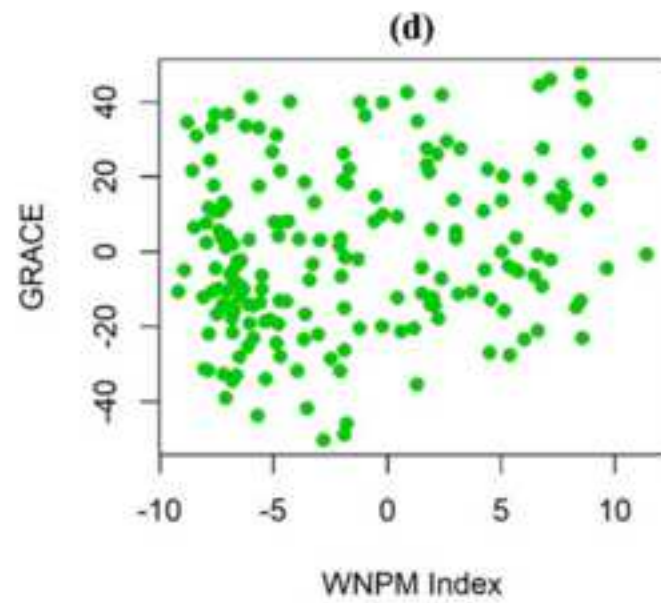
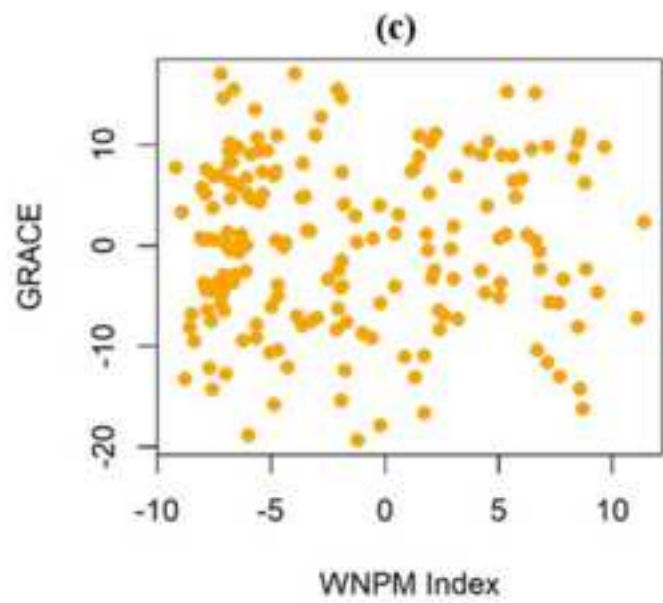
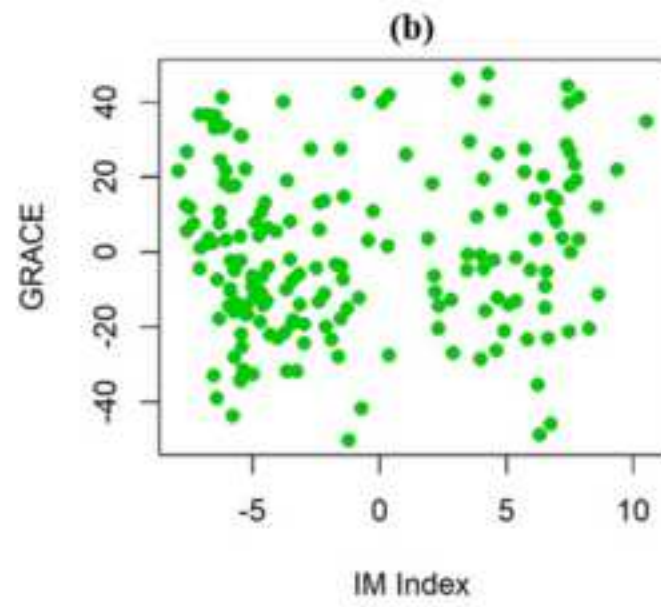
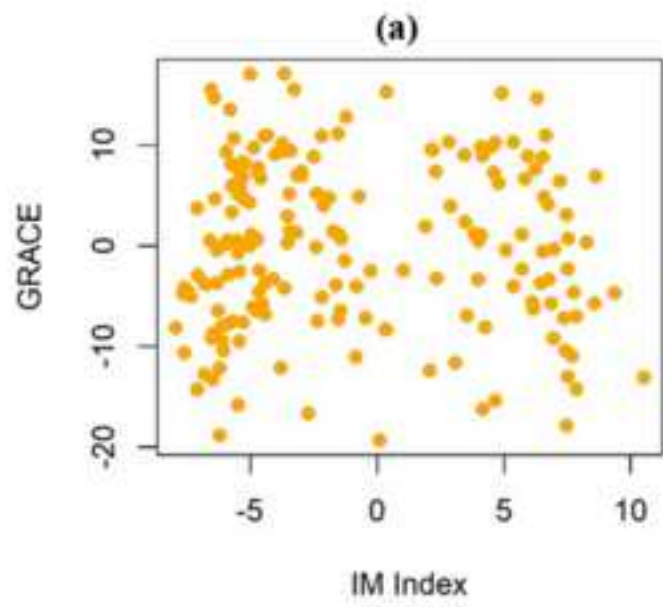
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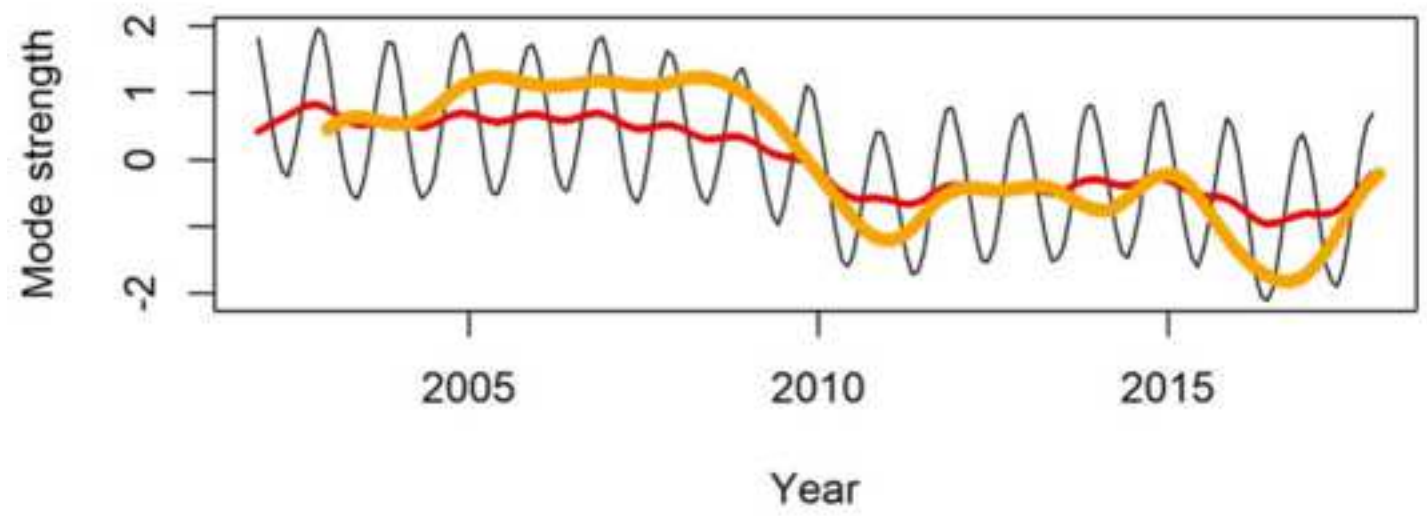
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(a) Modes 2+3 IMV



(b) Modes 2+3 WNPMV

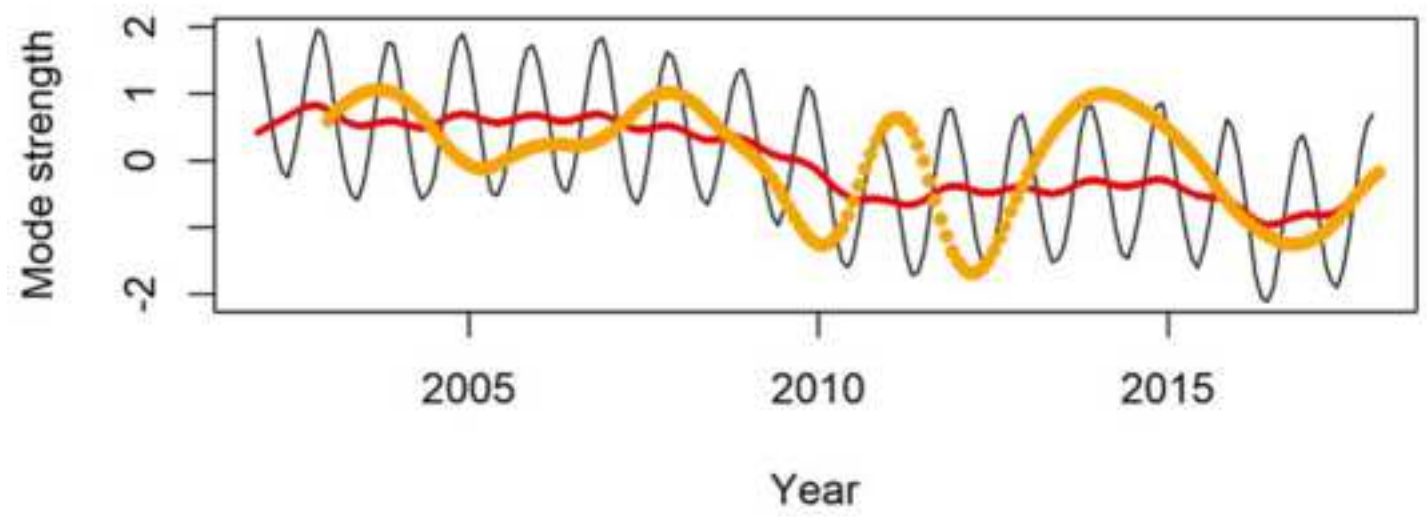
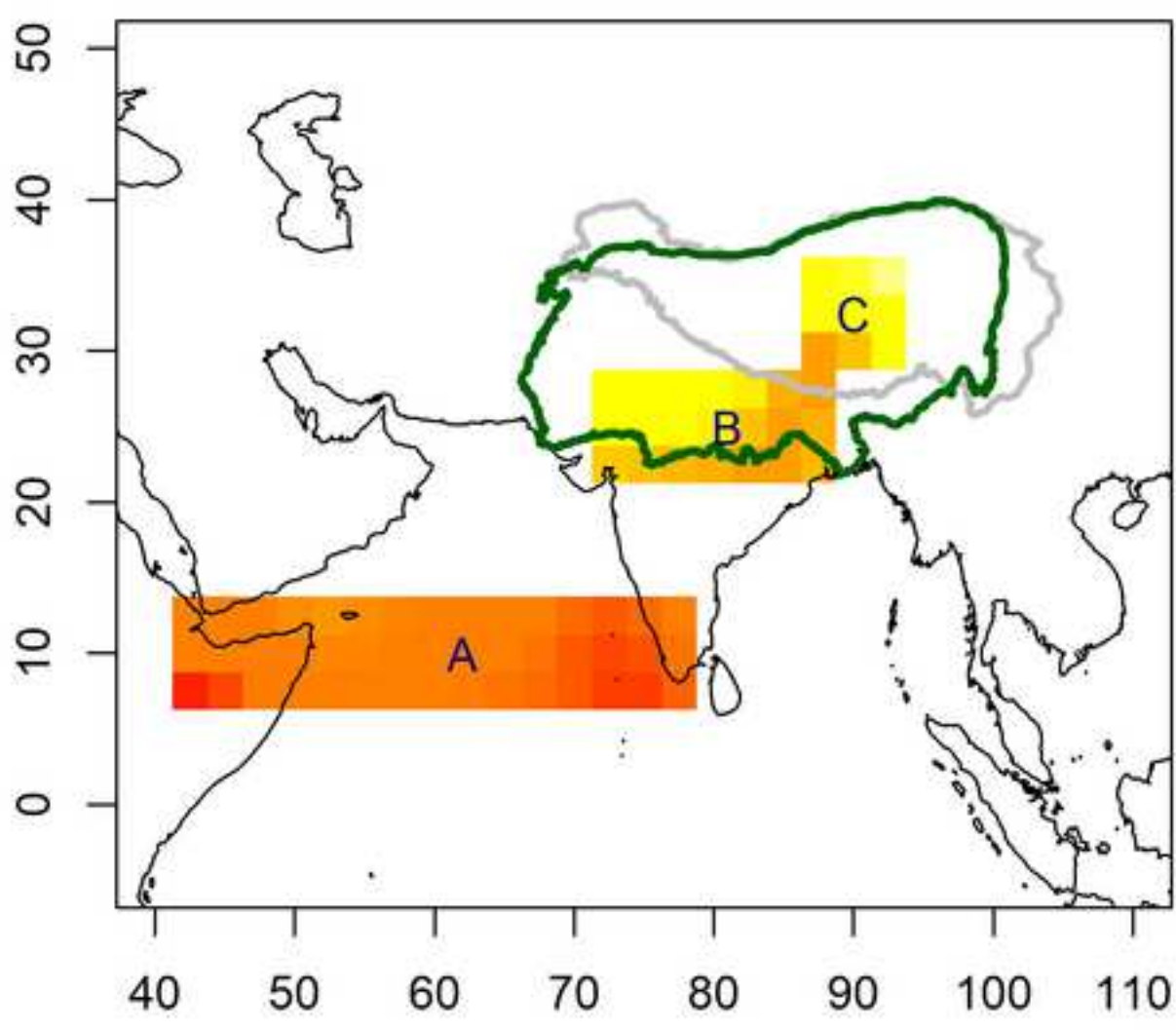


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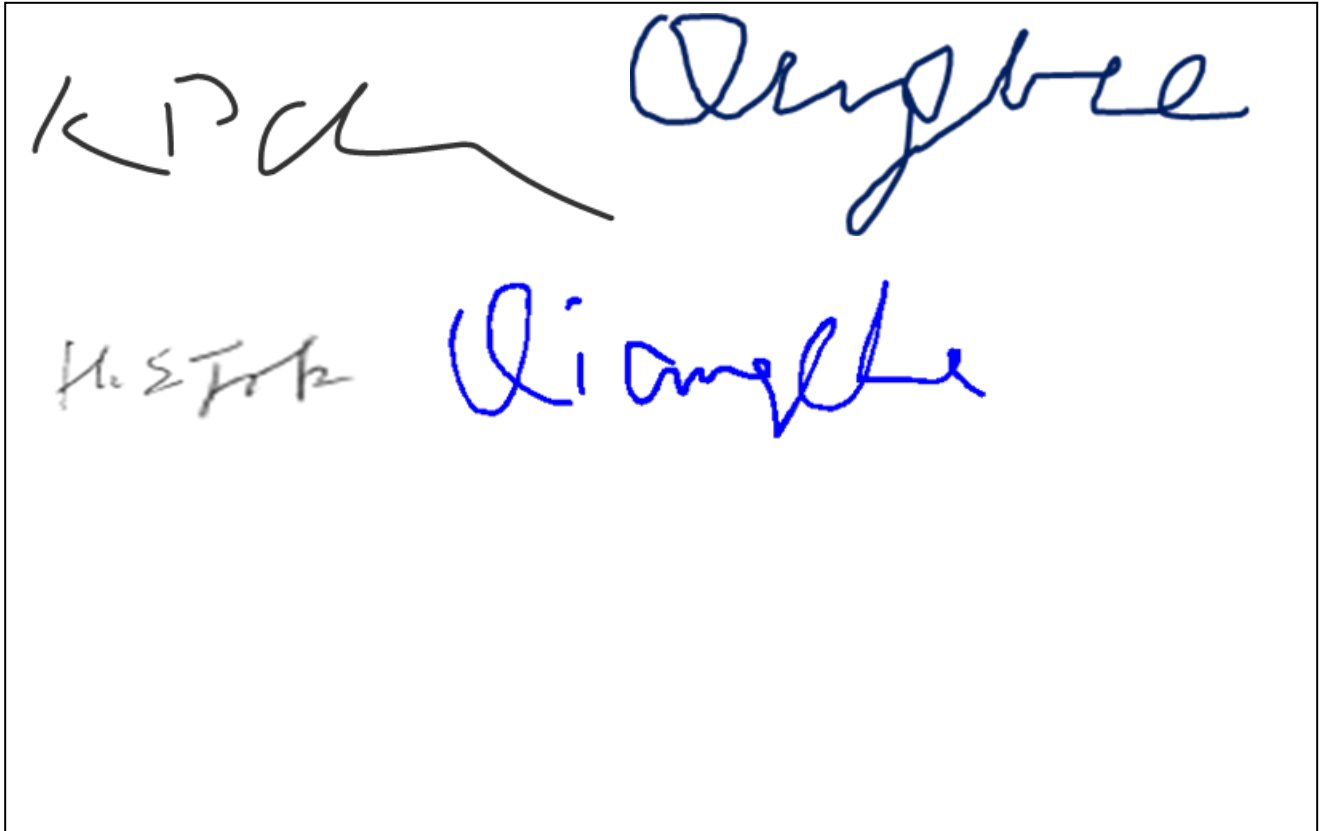
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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:



The image shows a rectangular box containing handwritten signatures. The top row features two signatures in black ink: 'KIP' followed by a stylized flourish, and 'Dunghbee'. The bottom row features two signatures in blue ink: 'H. S. Fok' followed by 'Lianghe'.