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1 **Impact of anthropogenic climate change on the East Asian summer monsoon**

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## ABSTRACT

6 The East Asian summer monsoon (EASM) is important for bringing rainfall  
7 to large areas of China. Historically, variations in the EASM have had major  
8 impacts including flooding and drought. We present an analysis of the impact  
9 of anthropogenic climate change on EASM rainfall in Eastern China using a  
10 newly updated attribution system. Our results suggest that anthropogenic cli-  
11 mate change has led to an overall decrease in total monsoon rainfall over the  
12 past 65 years, and an increased number of dry days. However the model also  
13 predicts that anthropogenic forcings have caused the most extreme heavy rain-  
14 fall events to become shorter in duration and more intense. With the potential  
15 for future changes in aerosol and greenhouse gas emissions, historical trends  
16 in monsoon rainfall may not be indicative of future changes, although extreme  
17 rainfall is projected to increase over East Asia with continued warming in the  
18 region.

## 19 **1. Introduction**

20 The East Asian summer monsoon (EASM) brings much needed water for agriculture to most  
21 of Eastern China. In recent decades southern provinces of China have experienced an increased  
22 frequency of severe flooding during the monsoon season. In contrast northern provinces of China  
23 have experienced an increase in severe summer droughts (for details of the northern drought /  
24 southern flood pattern see, for example, Qian and Zhou (2014), also see FloodList Copernicus  
25 project for examples, <http://floodlist.com/tag/china>). Understanding changes in past and future  
26 monsoon rainfall patterns can have important implications for water management and urban plan-  
27 ning.

28 The Clausius-Clapeyron relation states that the atmosphere can hold 7% more moisture per  
29 degree of warming. Basic physical expectations are that a warmer world should experience in-  
30 creased amounts of rainfall. A simple interpretation of the Clausius-Clapeyron relation is that  
31 the total quantity of rainfall should increase by 7% per degree of warming globally. However,  
32 in reality different surfaces heat at different rates, and in the case of anthropogenically induced  
33 global warming, greenhouse gases do not cause the atmosphere to be heated equally at all levels.  
34 Additionally, the emission of aerosols can change cloud formation properties, alter the locations  
35 of cloud nucleation sites, and cause localised cooling. Changes in chemistry and thermodynamics  
36 mean that increases in temperature may not necessarily lead to a uniform increase in precipitation  
37 in all locations or at all intensities of rainfall.

38 Heating of the lower troposphere as a consequence of increased concentrations of well mixed  
39 greenhouse gases (GHGs) leads to an increase in the height of the tropopause. GCM-based studies  
40 have argued that warming will cause increases in cloud height and stronger convection as a result  
41 (see Fowler and Hennessy 1995; Mitchell and Ingram 1992; Trenbeth et al. 2003). Other studies

42 have argued that surface warming leads to decreases in convective mass fluxes with the heating of  
43 the upper troposphere. It is instead argued that increases in horizontal transport due to an enhanced  
44 pattern of evaporation minus precipitation will cause increased convergence (e.g. Held and Soden  
45 2006). With an increased moisture content of the air, stronger convection or convergence will lead  
46 to more severe storms with higher hourly and total rainfall (Fowler and Hennessy 1995; Trenbeth  
47 et al. 2003; Held and Soden 2006).

48 Several studies of global rainfall trends have found that global annual mean and total precip-  
49 itation has increased by 1–3% per degree of warming (e.g., Allen and Ingram 2002; Wu et al.  
50 2013; Donat et al. 2016). At the same time extreme rainfall, defined by upper decile daily total or  
51 Rx1day, has increased by 6–7% per degree of warming (e.g., Trenbeth et al. 2003; Westra et al.  
52 2013). The increase in extreme heavy rain is often found to be at the expense of light rain, with  
53 studies finding a decrease in the number of light rain days, or total rain from light rain events,  
54 coinciding with increased totals or frequency of heavy rain (e.g., Trenbeth et al. 2003; Ban et al.  
55 2015; Allen and Ingram 2002).

56 Regional changes in rainfall totals and a changing distribution of rainfall between light and  
57 heavy events are also observed. In the current study we focus our attention on China. The annual  
58 rainfall climatology of China can be broadly split into two halves, a cold, dry winter monsoon  
59 from October to March, and a warm, wet summer monsoon from April to September. During the  
60 winter monsoon continental cold, dry air flows southwards from high latitudes, bringing a cold,  
61 dry winter. During the summer monsoon, warm moist air flows from the ocean to the south of  
62 China and converges with the cool dry air to the north. The convergence causes the formation of  
63 a rain band over the Indochina peninsula in China, and as the summer season progresses the rain  
64 band moves steadily northwards over Eastern China (and is known as the Meiyu), eventually as  
65 far north as Japan (where it is referred to as the Baiyu) and Korea (where it is referred to as the

66 Changma). Towards the end of the summer the rain band then retreats southwards (for a summary  
67 of the characteristics of the East Asian summer monsoon see Yihui and Chan 2005; Hsu et al.  
68 2014; Xue et al. 2015).

69 As mentioned above, in recent years Southern China has seen more frequent incidents of flood-  
70 ing and Northern China has seen more frequent severe droughts during the monsoon season when  
71 compared to historical monsoon seasons. Changes in monsoon total rain, and changes in circu-  
72 lation patterns which dictate the most northern extent of the Meiyu front each year have been  
73 correlated with modes of natural variability, such as the Pacific Decadal Oscillation (PDO) (Zhu  
74 et al. 2011; Qian and Zhou 2014; Qian et al. 2014). Several studies have also noted changes in  
75 total summer rain which coincide with the increasing trend in global temperature (Liu et al. 2005;  
76 Zhai et al. 2004; Su et al. 2006; Fu et al. 2008), and some studies suggest links with local emis-  
77 sions of anthropogenic aerosols (e.g. Qian et al. 2009; Fu and Dan 2013; Deng and Xu 2015).  
78 Many studies also note a change in character of summer rainfall in Eastern China, with increases  
79 in numbers of heavy rain days and decreases in numbers of light rain days reported (Zhai et al.  
80 2004; Liu et al. 2005; Fu and Dan 2013; Fu et al. 2008).

81 In this study we examine changes in the East Asian Summer Monsoon (EASM) rainfall over  
82 China using an ensemble of simulations from an atmosphere-only climate model representing  
83 present-day conditions with anthropogenic influences, and comparing these to an ensemble rep-  
84 resenting conditions without anthropogenic influences. We compare characteristics of light and  
85 heavy rain during the monsoon in model experiments with and without climate change and com-  
86 pare our results with those of previous observational studies.

## 87 **2. Data**

88 We use a model ensemble from HadGEM3-A-N216, run in the atmosphere-only mode with  
89 prescribed historical sea surface temperatures (SSTs) from HadISST1 (Rayner et al. 2003). The  
90 resolution is approximately  $0.5 \times 0.8$  degrees, equivalent to  $\sim 50$  km at the latitude range covered  
91 by China. The ensemble contains 15 members which include both anthropogenic and natural forc-  
92 ings (denoted ALL) from 1960-2015. This is compared with an ensemble of 15 runs of the same  
93 model which contain only natural forcings (denoted NAT), in which the SSTs have been adjusted  
94 to remove anthropogenic warming. This anthropogenic warming is calculated from the difference  
95 between the mean patterns derived from ALL and NAT simulations in 19 model ensembles from  
96 CMIP5 (Taylor et al. 2012). This pattern of SSTs is subtracted off the SSTs for the ALL experi-  
97 ment to provide the SSTs used in the NAT experiment. We also adjust the sea-ice concentration  
98 for the NAT experiment using simple empirical relationships between SSTs and sea-ice concen-  
99 trations. These methods and full details on model experiment setups are described in Christidis  
100 et al. (2013) and Ciavarella et al (2017, in prep).

101 To verify the model output we use the APHRODITE observational gridded daily precipitation  
102 dataset for East Asia (Yatagai et al. 2012). This dataset runs from 1960-2007, and is gridded to  
103 approximately the same resolution as the model ( $0.5 \times 0.5$  degrees). Han and Zhou (2012) compare  
104 the APHRODITE dataset to daily rainfall records from 559 rain gauges spread over China. They  
105 find that the APHRODITE data shows very similar rainfall amounts for mean variables, such as  
106 seasonal total, and accurately characterises the progression of the seasonal rain band. However  
107 they find that the gridding of spatially sparse station data in APHRODITE leads to underestimates  
108 of precipitation intensity and overestimates of precipitation frequency compared to the station data.  
109 They show that annual mean heavy rainfall totals are underestimated and light to moderate rainfall

110 totals are overestimated in the gridded data. A large difference is also found between the station  
111 and APHRODITE data for spatial patterns of trends in intense rainfall, and that the APHRODITE  
112 data underestimate trends in the recent northern drought / southern flood pattern compared to  
113 station data. With these limitations in mind, we use the APHRODITE data for model verification  
114 of seasonal rainfall characteristics, and focus on the model output for examining trends in rainfall  
115 and changes in extreme rainfall characteristics.

116 For consistent comparison, we regrid both the observations and model to an identical 1x1 degree  
117 grid, taking daily area means over the cells within the 1x1 degree grid. A map of the mean and  
118 maximum numbers of stations per grid cell for APHRODITE between 1960 and 2007 is shown in  
119 the top row of Figure 1. As is clear in the figure, in Western China station coverage is spatially  
120 very sparse. Additionally, being a desert, the monsoon does not reach this region, so we exclude  
121 Western China from our analysis.

### 122 **3. Model evaluation and climatology**

123 For this study we define the monsoon season to be from the beginning of April to the end of  
124 August. Figure 2 shows the climatological rainfall, averaged over 1960-2000, for the monsoon  
125 season from 5-day total rainfall for 4 time slices throughout the monsoon season. Being a multi-  
126 decadal average the detailed features of the monsoon do not appear very strongly due to their  
127 spatial variation between years. However some indication of the general location of the Meiyu  
128 front can be seen in both observations and model. The model reproduces fairly well the spatial  
129 location of the observed rainfall and the progression of the locations of high and low rainfall  
130 throughout the monsoon season. However the model consistently overestimates the total rainfall.  
131 When normalised to the observations (dividing out by the East China area-mean ratio of observed

132 total to model total, right hand column in Figure 2) the model appears qualitatively similar to the  
133 observed rainfall patterns.

134 Figure 2 also shows the climatological (1960–2000) mean total seasonal rainfall and climato-  
135 logical seasonal maximum daily rainfall. As is again clear in this figure, the model reproduces  
136 quite well the spatial patterns of rainfall but tends to over-predict rainfall totals. When normal-  
137 ized the model mean appears qualitatively similar spatially to the observations. We use the raw  
138 (non-normalized) model output for the rest of our evaluation and for our analysis of the monsoon.

139 We group areas of China into climatologically similar regions, indicated in Figure 1. We exclude  
140 regions with very low numbers of observation stations. These regions also tend to be in the desert  
141 parts of China and therefore receive very little rainfall annually and are not climatologically subject  
142 to rainfall as a result of the monsoon.

143 The bottom rows of Figure 1 show the intensity distribution of daily precipitation total for all  
144 years between 1960-2000. This figure indicates how much daily total rainfall contributes to the  
145 total monsoon seasonal rain. For the central 4 regions the model reproduces the shape of the  
146 distribution well. However for all the regions the model peak of the distribution of daily rainfall  
147 contribution is at a somewhat larger value than is observed, and shows a fatter tail at the high daily  
148 total end of the distribution. However, as previously noted, the APHRODITE gridded data may  
149 underestimate the heavier end of the daily precipitation distribution. This could lead to a skewing  
150 to the lighter end of daily precipitation in the observations. Alternatively it could be that the model  
151 systematically overestimates daily rainfall in Eastern China during the monsoon season.

152 Figure 3 shows the 1960-2000 climatology of 5-day consecutive (non-overlapping) total rain  
153 throughout the monsoon season for the regions shown in Figure 1. As in earlier figures, the model  
154 reproduces the spatial patterns and timing of the monsoon rainfall fairly well but overestimates the  
155 total rainfall. For three northern regions the model spread encompasses the observed totals. For

156 SEC the model spread and mean are close to the observed values but generally for the southern  
157 regions the mean 5-day totals are greater than observed.

158 The reported under-estimation of extreme rainfall in APHRODITE (Han and Zhou 2012) may  
159 contribute to the discrepancy between observations and models. We also examine this claim using  
160 a small number of publicly available station data for China, which have undergone basic quality  
161 control. In Figure 4 we show the same as Figure 3 but for one station per region for 6 of 7 regions,  
162 compared with grid cells containing the station location in the model and APHRODITE data -  
163 station locations are indicated in the figure. Whilst the station is a point source, and the gridded  
164 data is a representation of a larger area this comparison gives a reasonable idea of how well the  
165 model and gridded observations perform. In Figure 4 it is generally clear that the station data 5-day  
166 rainfall totals are slightly higher than the APHRODITE data. As noted in Han and Zhou (2012),  
167 in Figure 4 the APHRODITE data shows notably lower total rain for heavy rainfall days than is  
168 recorded in the station data. This figure shows the model data to be more similar to the station  
169 data than the APHRODITE data. This comparison provides some crude measure of observational  
170 uncertainty. While the station data is a point source, estimates of 5 day total rainfall may be less  
171 biased than the larger grid box average from APHRODITE.

172 When compared to APHRODITE our model reproduces the main features of the monsoon fairly  
173 accurately. Comparison with data from a few stations shows that the model also reproduces ex-  
174 treme rainfall. Although the model seems to generally overestimate rainfall totals compared to the  
175 observations, the offset between the two is fairly consistent, so for examining trends in monsoon  
176 rainfall the model should be adequate.

177 It is interesting to note that the model used here can reproduce the main features of the EASM,  
178 including the Meiyu front and its progression. This has been challenging for models in the past  
179 including many CMIP5 generation models. The improved resolution of models from N96 (as used

180 by most CMIP5 models) to N216 (as used by our model) has been shown to produce more realistic  
181 precipitation globally (Demory et al. 2014) and regionally (Schiemann et al. 2014; Vellinga et al.  
182 2016), and more realistic monsoon systems (Johnson et al. 2016). Our model uses prescribed  
183 SSTs and sea ice coverage, one advantage of which being that it will capture many ongoing large-  
184 scale modes of natural variability, such as El Nino. This and the ‘correct’ forcing from sea surface  
185 temperature will allow a more accurate monsoon to be produced for a specific year than a coupled  
186 model. The physical realism of our model make it a suitable tool for studying changes in the  
187 characteristics of the EASM.

#### 188 **4. Analysis of trends in monsoon rainfall**

189 We calculate anomalies with respect to the 1960-1979 mean value for the each of ALL and  
190 NAT and observations to illustrate trends in monsoon rainfall. Anomalies are only calculated for  
191 illustrative purposes, and do not inform the results shown below. We choose this baseline which  
192 is shorter than the more commonly used 1961-1990 baseline, in order that the reader might see  
193 changes in the metrics examined by eye.

194 The time series in Figure 5 shows the seasonal total monsoon rain anomaly for the SEC region,  
195 and we use SEC as an example for the rest of the results presented. No clear trend is seen for the  
196 time series of the seasonal total monsoon rain and the interannual variability is large for all of the  
197 regions indicated in Fig 1. There is no clear difference between the ensemble means of the ALL  
198 and NAT forcings experiments for most of the timeseries, however there is a difference between  
199 the two for the most recent 5 years (2010-2015). The time series of mean daily total rainfall also  
200 shows no trend and large variability (not shown), and similarly variable time series, with lack of  
201 clear trends, are found for mean 5-day total rain, and maximum 5-day total rain. Since the time  
202 series data is very noisy, and trends are likely to be well within the internal variability, we focus

203 on the differences between the distributions of the ALL and NAT ensembles for the most recent  
204 15 years when presenting quantitative results.

205 Figure 5 also shows the total number of dry days in the monsoon season (rainfall total less than  
206 1mm/day). For all regions the ALL forcings ensemble mean shows an increased number of dry  
207 days compared to the NAT ensemble mean, and the difference between the two ensembles appears  
208 greatest in more recent years suggesting an increasing trend in dry days in the ALL model. The  
209 variability of the model and the observations are again quite large and trends (if present) are not  
210 very clear. Given that the monsoon total rain shows no clear change, an increase in the number of  
211 dry days during the monsoon could imply an increase in rainfall total per day on wet days.

212 Previous studies have noted changes in observed rainfall when the season is divided up into  
213 deciles of daily total rain (e.g. Liu et al. 2005; Fu and Dan 2013; Fu et al. 2008). For our model  
214 ensemble we divide all the wet days (total rain  $\geq 1$  mm/day) in the monsoon season into deciles of  
215 daily total rain - where each decile contains 10% of the total seasonal rainfall. We define the decile  
216 bin edges using all the members of the NAT ensemble between 1960-2015. The upper and lower  
217 limits for each bin are then applied to the ALL forcings ensemble. Figure 6 shows the change  
218 in total rain in each decile for the last 20 years of data with respect to the 1960-1979 baseline  
219 climatology. Some regions show changes in the distribution of rainfall totals between deciles for  
220 the ALL ensemble mean. For the southern regions a clear increase can be seen in the lowest decile  
221 (bottom 10 % daily total rain), and at the same time a decrease in the total rain in the upper deciles  
222 for the ALL ensemble with respect to the NAT ensemble (see Fig 6). A decrease in rainfall from  
223 upper decile days and an increase in rainfall from lower decile days is the opposite of what is  
224 generally reported in the literature (e.g. Liu et al. 2005; Ma et al. 2017), however the literature  
225 reports results for observations which end in 2000-2006.

226 We also analyse the distribution (PDF) of daily totals (and numbers of days) within the 1st and  
227 10th deciles (ie, the top and bottom 10% daily total rainfall). For the 10th decile, comparing  
228 the ALL and NAT forcings experiments, the ALL ensemble has lower total rainfall and a lower  
229 number of days of rain, however the PDF (Fig 6) also shows a fatter tail at high values of mean  
230 rainfall per day. So even though the total rainfall in the 10th decile is less in the ALL ensemble  
231 than the NAT ensemble, the total rain in individual days is shifted to higher values (see Fig 6). We  
232 discuss this further below.

233 In reality rain falls during storms, which may last several days. We divide the monsoon season  
234 up into storms, or events, of n-days in duration. An event is defined as a number of consecutive  
235 days where each day has total rainfall greater than 1 mm. The duration of an event is **n\_days**, the  
236 total rain which falls during an event is **n\_day\_tot**, and the mean rainfall per day during an event  
237 is **intens** (see Burke et al. 2016). We divide up the monsoon into events for each grid cell.

238 In a time series of mean and maximum annual n\_days, n\_day\_tot and intens (not shown) there is  
239 no clear trend, no clear separation between ALL and NAT ensemble means and large variability.  
240 As illustrated above, changes in monsoon rainfall are more pronounced at the extreme light and  
241 heavy ends. In our previous paper (Burke et al. 2016) we found that for rainfall events in May 2015  
242 with high n\_day\_tot, intens increases and n\_days decreases in the ALL forcings ensemble compared  
243 to NAT. We examine the changes in n\_days and intens for the 95th percentile n\_day\_tot, where the  
244 95th percentile is defined from the NAT ensemble for events between 1960-1979. Figure 7 shows  
245 the time series (percent anomaly) of n\_days and intens for events in the 95th percentile of n\_day\_tot  
246 - both figures show 5 year means in order to show the signal more clearly without so much natural  
247 variability. In this figure a trend can be seen for increased intens and decreased n\_days with time,  
248 and a shift in the spread of the ALL ensemble in the same direction.

249 We remind the reader that our chosen threshold for a wet or rainy day is 1 mm/day. Given that  
250 this threshold for a rainy day is set relatively low, this will inevitably lead to us recording long  
251 duration events using our n\_days method. The most extreme consequence of this being that our  
252 rainfall events can last weeks; a continuous rainfall event of this magnitude would probably be  
253 unphysical in reality. Given the temporal resolution of data available to us we are not able to  
254 examine the ‘real’ duration of individual rain storms. However, the number of consecutive days of  
255 rain is an interesting metric with regards to flooding. The change in number of consecutive days  
256 of rain and the total rainfall in those days is also informative as to how the nature of rainfall during  
257 the monsoon season is changing as a result of anthropogenic forcings. As the EASM season  
258 progresses, the rain band (Meiyu front) moves northwards across East China and later retreats  
259 southwards again (as described in the introduction). As such most regions of East China will  
260 experience multiple wet and dry spells throughout the season. Our n\_days method allows us to see  
261 how anthropogenic forcings change in the progression and duration of the wet and dry spells.

## 262 **5. Change in likelihoods of extreme rainfall due to anthropogenic climate change**

263 We examine change in likelihood of the metrics for which we can see differences between the  
264 ALL and NAT experiment output described above using the most recent 20 years of model data  
265 (1996-2015). The change in probability,  $\Delta P$  (sometimes referred to as ‘risk ratio’ in the literature),  
266 is given by  $\Delta P = P(\text{ALL})/P(\text{NAT})$ , where  $P(\text{ALL})$  and  $P(\text{NAT})$  are the probability of a metric ex-  
267 ceeding a given threshold in the ALL and NAT ensembles respectively. For each metric presented  
268 we define a threshold based on the NAT ensemble - these thresholds are the mean, 10th percentile  
269 or 90th percentile of the NAT ensemble depending on the metric examined. As such  $P(\text{NAT})$  will  
270 be equal to 0.5 where we define our threshold to be the mean of NAT (etc).

271 P(ALL) is calculated by fitting a probability distribution function to the histogram of the variable  
272 considered, and taking the area under the curve above (or below) the threshold defined by NAT.  
273 This is illustrated in the PDF plots in Figures 5–7. We fit a gamma distribution to the normalized  
274 histogram for the variable considered, (as illustrated in the figures) using a maximum-likelihood  
275 estimation fitting routine (gamma.fit - freely available in scipy.stats). There are a minimum of  
276 300 data points in each fitted histogram (15 members x 20 years x points per year for metric  
277 in question), so there is sufficient data for a reliable fit - by eye the curves appear to fit well.  
278 We test the goodness of fit by calculating  $\Delta P$  from the area under each histogram before fitting,  
279 and compare with the value of  $\Delta P$  from the fits to the histograms. We find the values of  $\Delta P$   
280 from the histogram to be the same as those from the gamma fit to within 2% (ie  $\Delta P(\text{gamma fit})/$   
281  $\Delta P(\text{histogram})=1.00\pm 0.02$ ,  $SD=0.05$ ). The results from calculating  $\Delta P$  with and without fitting  
282 are close enough that we are confident of the appropriateness of the gamma fit to represent the  
283 distribution of the data. These values derived with and without fitting are similar enough, and  
284 enough data is available to sample the distribution of values well, that fitting may not actually be  
285 necessary for examining extremes in this case.

286 The maps in figs 5–7 also indicate which grid cells have  $\Delta P$  which is significant at the  $2\sigma$   
287 level. The statistical significance of  $\Delta P$  is determined by bootstrapping the data and fitting the  
288 resulting histogram with a PDF from which  $\Delta P$  is calculated. The bootstrap is performed 1000  
289 times for each grid cell (with replacement). For some of the figures there are a large number of  
290 grid cells which aren't significant at  $2\sigma$ , and at a  $1\sigma$  level the picture is generally the same but  
291 with the addition of the grid cells along the coastlines also being significant. However, given the  
292 contiguous large areas showing similar changes in distribution, a lack of statistical significance in  
293 individual grid cells may be indicative of the presence of weak trends. We report area mean values  
294 for  $\Delta P$  and the change in the mean absolute value (also 10th and 90th percentile for monsoon total

295 rain and number of dry days respectively) for each variable and each region in Table 1. The change  
296 in mean absolute value is defined as the difference between the mean of the NAT and the mean of  
297 the ALL ensembles (similarly for the value of 10th and 90th percentiles). As is clear in the table,  
298 when averaged over larger areas the values of  $\Delta P$  and the changes in absolute values of variables  
299 measured are indeed statistically significant in most cases.

300 Figure 5 shows  $\Delta P$  maps for the monsoon total rain and the number of dry days during the  
301 monsoon. Despite no clear difference between ensemble means and no clear trends being seen in  
302 the time series, the change in the probability distribution function of monsoon total rain between  
303 the ALL and NAT forcings ensembles is statistically significant (see also Table 1). Over all of East  
304 China the seasonal total rain is likely to be less, and the number of dry days during the monsoon  
305 is likely to be greater in the ALL ensemble compared to the NAT ensemble. The total rainfall  
306 during the monsoon season is 10–40% ( $\Delta P = 1.1$ – $1.67$ ) more likely to be below the NAT ensemble  
307 average in the ALL ensemble than the NAT ensemble. This is more severe in the south of the  
308 region of China examined than the north, see figure 5. The area-mean value of total monsoon  
309 rainfall is found to be 45mm less in the ALL ensemble compare to NAT. The decrease in mean  
310 annual rainfall ranges from tens of mm in northeast China to  $\sim 100$  mm or more in southern areas  
311 (the maximum decrease for an individual grid cell examined is 291mm). The area-average  $\Delta P$  for  
312 total monsoon rainfall to be below the 10th percentile defined by NAT is 1.1, and the value of the  
313 10th percentile seasonal total is decreased by 49mm in the ALL-forcings world compared to the  
314 NAT-forcings world (East China area average).

315 Similarly the likelihood of the number of dry days in the season being above the NAT average is  
316  $\Delta P=1.4$ – $2$  in most of southern and eastern China, with an increase in the mean number of dry days  
317 of 3.6 days in the ALL ensemble. The area-mean likelihood of the number of dry days exceeding

318 the 90th percentile of the NAT ensemble is  $\Delta P=1.9$  in a world with climate change, with the 90th  
319 percentile number of dry days increased by 3.4 days in the ALL-forcings ensemble.

320 Figure 6 shows  $\Delta P$  maps for bottom 10% and top 10% daily rainfall totals (first and tenth  
321 deciles), and the mean rainfall per day in the top 10%. On average, there is likely to be more  
322 rainfall in the first decile and less rainfall in the 10th decile in the ALL ensemble compared to  
323 NAT. However the rainfall total on individual days in the 10th decile is likely to be greater in the  
324 ALL-forcings world - whilst this change is not statistically significant for the majority of individ-  
325 ual grid cells, it is statistically significant when we average over larger areas (see Table 1). The  
326 strongest results for this are in South East China - for the total rain in the 1st decile being above  
327 the NAT average  $\Delta P=1.2$ , and for mean total rain in the tenth decile being below the NAT aver-  
328 age  $\Delta P=1.25$ . However the likelihood of rainfall per day in the 10th decile being above the NAT  
329 mean in this area is  $\Delta P=1.1$  in the ALL ensemble. So in this region, anthropogenic forcings may  
330 be causing shift to more light rain and less heavy rain in the season, but even though heavy rain  
331 days are more infrequent, the total rainfall per day on heavy rain days is increased. The likelihood  
332 changes we find for the number of days in each decile are similar in value to those reported above  
333 for total rain per decile. However the absolute changes in number of days in each decile are of  
334 the order 0.1-0.5 days increase, or 0.5-1.0 days decrease, for first and tenth deciles respectively. It  
335 could be argued that over the period of time examined, 1960–2015, this change is small enough to  
336 not be observable.

337 Figure 7 shows  $\Delta P$  maps for the duration ( $n\_days$ ) and intensity ( $intens$ ) of rainfall events in the  
338 95th percentile of  $n\_day\_tot$ . For a NAT-forcings world average 95th percentile  $n\_day\_tot$  event, in  
339 an ALL-forcings world the event is 1.3 times (area average) more likely to be shorter in duration,  
340 and the daily total rain within each day of the event is 1.1 times more likely to be greater. On area-  
341 average, these events will be 1.8 days shorter, with the decrease in duration being more pronounced

342 in the south than the north (see figure). The mean rain per day in these extreme events is increased  
343 by 1 mm/day in the ALL ensemble compared to NAT. Thus we have found evidence that the  
344 intensity of the most extreme rainfall events is expected to increase due to anthropogenic forcings.

## 345 **6. Discussion**

346 Under anthropogenic forcings the model predicts that there is, on average, a decrease in the total  
347 monsoon rainfall, an increase in the number of dry days, an increase in the total rain which falls in  
348 the 1st decile of daily totals and a decrease in the total rainfall in the 10th decile of daily total rain.  
349 This gives a picture of a generally dryer monsoon. However, for extreme heavy rainfall events a  
350 different picture is given. The results show an increase in total rain per day in the 10th decile of  
351 daily total rain, and for the 95th percentile of n-day-total rainfall in events as defined above, the  
352 mean rainfall per day is increased and the number of days over which the rain falls is decreased. So  
353 whilst the total seasonal rain is generally reduced, and the distribution of daily total rain is shifted  
354 towards the lighter end, for heavy rain events the rainfall per day is increased and the duration of  
355 heavy rain events is decreased.

356 The statistical significance of the changes reported per grid cell is strong for the general drying  
357 changes - monsoon total rainfall, number of dry days, increase in 1st decile days, shortening  
358 in duration of extreme events. The statistical significance per grid cell is weaker for increased  
359 tenth decile rain per day and increased intensity of heavy rain events. Figures 6 and 7 show  
360 comparatively few grid cells are significant at  $2\sigma$  for these metrics compared to the drying metrics  
361 (at  $1\sigma$  the coastal grid boxes also appear significant, but otherwise the figures are very similar,  
362 not shown). However, for regional averages on most metrics the results are statistically significant  
363 (see Table 1). The heavy rainfall changes are smaller in magnitude compared to the changes for

364 drying metrics for both grid cells and regional means. This suggests that the increase in extremes  
365 is a smaller effect than the overall drying.

366 We have examined changes in the monsoon season, considering all the days from the beginning  
367 of April to the end of August as being in the season. As illustrated in figure 3, the rainfall within the  
368 season is very variable between dates and locations. It may be that our examination misses detail  
369 on shorter timescales and that changes in extremes are more or less pronounced on the monthly  
370 timescale than that reported for the whole season. We also do not examine changes in the timing  
371 or spatial extent of the monsoon season.

372 We point out that our results are for model data and represent changes in likelihoods between  
373 model ensembles with and without anthropogenic climate change. As such the results presented  
374 here are predictions of the changes in monsoon rainfall as a result of anthropogenic forcing, which  
375 we might expect to see in observations.

376 Whilst we have carried out some verification with the observations available to us, we suspect  
377 that the observations we have for this region are imperfect (as illustrated in figure 4). In order to  
378 verify the model and results presented here more detailed and up to date observational studies will  
379 be required. Unlike many CMIP5 generation models which struggle to reproduce extreme rainfall  
380 observed in reality, the model set-up used is able to produce the extremes of rainfall which are  
381 observed, and tends to over rather than under predict the extremity and frequency of heavy rainfall  
382 (however the observed gridded data we compare to may underestimate extreme rainfall).

### 383 *Physical basis and comparison with previous studies*

384 In recent years there have been reports of a southern flood / northern drought pattern during the  
385 summer monsoon (see introduction). A dryer monsoon season could easily lead to drought, and  
386 short intense rainfall bursts can lead to flooding. Long duration rainfall is generally needed to

387 alleviate droughts, so short but heavy rainfall events, once over, may allow a drought to persist.  
388 Examination of the mechanism which would cause extended drought over northern China but  
389 recurring flooding over southern China is outside of the scope of this study.

390 Several previous model-based studies discuss intensifying convection as a result of global warm-  
391 ing leading to increased heavy rainfall, and depletion of light rain at the expense of this heavy rain  
392 (e.g. Trenbeth et al. 2003). The proposed mechanisms for this change are that global warming can  
393 lead to enhanced convection processes, an enhanced water cycle and increased convergence (su-  
394 per Clausius-Clapeyron). The heavy rainfall as the result of these processes is more extreme than  
395 in a world without anthropogenic climate change, and the result of intense downpours is that the  
396 precipitable water column is emptied, inhibiting subsequent light rainfall (Fowler and Hennessy  
397 1995; Fisher and Knutti 2016; O’Gorman and Schneider 2009). The recent observational work  
398 of Fisher and Knutti (2016) shows that globally very heavy daily total rainfall events in the 95th  
399 percentile or greater are notably increasing in frequency and this is reflected in current climate  
400 models. Generally, recent observational studies of global rainfall trends report a slight increase in  
401 total rainfall (e.g. Wu et al. 2013), however for heavy rainfall a significant increasing trend is con-  
402 sistenty found (Donat et al. 2016; Westra et al. 2013; Ban et al. 2015; O’Gorman and Schneider  
403 2009).

404 Over the area of East China, in the upper decile of daily rainfall total we see some weak shift to  
405 larger rainfall per day values, but we do not see a reduction in light rain (1st–2nd decile daily total  
406 rain). Perhaps by selecting the 90th percentile, rather than the 95th or 99th we are only seeing  
407 hints of this trend in our only moderate results for heavy rain increase. Similarly for our 95th  
408 percentile n-day-total rainfall, we see some weak indication of increased daily total, but it is not  
409 as impressive as that reported for global daily totals.

410 On more local spatial scales, some previous observational studies also report an increase in  
411 heavy rain and a decrease in light rain over China. For example Ma et al. (2017), observe a  
412 decrease in total rain from light rain days, and an increase in total rain from heavy rain days. Their  
413 reported change in light rain is weak statistically, and their reported change in heavy rain is larger  
414 and statistically stronger.

415 Numerous observational studies have reported an increase in seasonal total rainfall over the  
416 period 1960-2000 for eastern China (Liu et al. 2005; Zhai et al. 2004; Wang and Zhou 2005; Su  
417 et al. 2006; Fu and Dan 2013; Fu et al. 2008; Qian and Qin 2007; Gemmer et al. 2003). However  
418 these changes are not uniformly spatially coherent, nor are the observed regions all defined to  
419 cover the same areas as each other, or as that examined here. Subsets of these works (Zhai et al.  
420 2004; Liu et al. 2005; Fu and Dan 2013; Fu et al. 2008; Su et al. 2006; Qian et al. 2009) also  
421 report increases in the number of heavy rain days and decreases in light rain days, and also with  
422 shifts in rainfall totals across daily deciles in a similar direction. The method by which deciles  
423 or thresholds for extreme rainfall totals are defined differs between most of these studies, being  
424 defined for individual seasons in some, and annually in others. The regions studied also vary  
425 between publications, and deciles and extremes may be defined as an area average or within sub-  
426 regions. Additionally, these studies tend to end in 2000, near the start of our current climatology  
427 and given that they end 15 years ago it would be interesting to see if the results that they present  
428 continue in more recent years. Similarly to the result presented here, the trends reported by most  
429 literature studies tend to be statistically weak and the data noisy - this is a frequent issue for studies  
430 of precipitation.

431 There are observational literature studies which are complementary to our findings. For exam-  
432 ple Xiao et al. (2016) examine the observed hourly peak total rainfall during the monsoon season.  
433 They find peak hourly rainfall is correlated with daily mean temperature, and that the number of

434 rain hours per day decreases with increasing temperature, with hourly precipitation extremes in-  
435 creased by 10% per degree increase of daily mean temperature. However they find daily extremes  
436 decrease by approximately the same amount - so extreme total rainfall is increasing but duration  
437 is decreased on the hourly timescale.

438 Liu et al. (2005) find a 10% decrease in frequency of precipitation events between 1960-2000.  
439 Zhai et al. (2004) also report a decrease in number of rain days over East China between 1950-  
440 2000. They also find the daily rainfall total in the 95th percentile has increased with time, and an  
441 increased frequency of 95th percentile rainfall days in South and Eastern China during the warm  
442 half of year. However they find no statistically significant change in annual rainfall total.

443 Precipitation is a notoriously difficult variable to measure accurately, perform trend analysis of,  
444 and detect changes in with any meaningful confidence. In the studies discussed above, several  
445 subtly different methods are used to detect changes in rainfall in subtly, but non-trivially, different  
446 ways. In an ideal world it would be beneficial to have a unified metric, or set of metrics by which  
447 changes in rainfall could be judged. This would help promote a clearer path to detecting and  
448 attributing changes and understanding what drives them.

#### 449 *Future changes*

450 With future reductions in aerosol emissions and a continued increases in greenhouse gas emis-  
451 sions, historical trends in monsoon rainfall may not be indicative of future changes (Christensen  
452 et al. 2013). CMIP5 (Taylor et al. 2012) RCP8.5 model projections predict that east China summer  
453 season (JJA) will become wetter in future (see figure 12.22 in IPCC AR5 Chapter 12, Collins et al.  
454 (2013)), with a projected increase of approximately 20% in seasonal rainfall total by the end of the  
455 century with respect to the mean of 1986-2005. The projected changes are likely due to increases  
456 in GHGs and reduction in aerosols. Additionally, in line with our historical results, the maximum

457 5-day precipitation and the number of consecutive dry days are projected to continue to increase  
458 for east China (see figure 12.26 of IPCC AR5 Chapter 12; also Chapter 14, page 1271, Christensen  
459 et al. 2013).

460 In line with our results for historical changes in rainfall, in future, in a world with increased  
461 global warming, we might expect to see more short intense rainstorms, increasing the possibility  
462 of flash flooding. However, there may be fewer days of rain between extreme rainstorms, which  
463 can lead to drought. Alleviation of drought requires rain over an extended period, the shortening  
464 of rainstorms means that drought may be exacerbated.

## 465 **7. Conclusions**

466 We have presented the results of a historical model ensemble with and without anthropogenic  
467 influence on the climate system. We verify our model against observed climatology and find that  
468 it can reproduce the main features of the EASM. The model shows that, in the anthropogenic in-  
469 fluence scenario, the EASM is generally dryer overall, with a decrease in total rain and an increase  
470 in dry days. However the anthropogenic influence model also shows an increase in the intensity  
471 of heavy rain events. These changes could lead to increased likelihood of flash flooding during  
472 rainstorms, but also an increased likelihood or severity of drought in some locations.

473 Historically a range of different results are found when examining observed rainfall in Eastern  
474 China during the summer and EASM season. These changes are not always consistent with those  
475 observed globally, which suggests localised forcings may be at play. However, given the range of  
476 methodologies and observed and modelled data available for investigating rainfall, this is an area  
477 which still warrants further study.

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586 **LIST OF TABLES**

587 **Table 1.** Results by regions as indicated in Figure 1. Probability ratio,  $\Delta P$ , values give  
588 the change in likelihood of the mean seasonal value of the variable considered  
589 for the ALL ensemble with respect to the NAT ensemble. The absolute change  
590 is the change in the value of the variable considered for ALL ensemble with  
591 respect to the NAT ensemble, for example, the mean seasonal rainfall total is X  
592 mm less. Results **not** statistically significant at  $2\sigma$  are highlighted in *italics*. . . . 29

593 TABLE 1. Results by regions as indicated in Figure 1. Probability ratio,  $\Delta P$ , values give the change in like-  
594 lihood of the mean seasonal value of the variable considered for the ALL ensemble with respect to the NAT  
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596 respect to the NAT ensemble, for example, the mean seasonal rainfall total is  $X$  mm less. Results **not** statistically  
597 significant at  $2\sigma$  are highlighted in *italics*.

Variable		NE	NCC	NEC	CW	SCC	SEC	SE
Total rainfall	$\Delta P$ mean	0.8±0.01	0.8± 0.01	0.9±0.01	0.9±0.03	0.6±0.03	0.8±0.01	0.6±0.02
	Mean change (mm)	-28.3±1.72	-34.9±2.26	-13.5±2.38	-13.3±4.62	-110.0±6.56	-72.9±4.12	-146.2±9.15
	$\Delta P$ 10th percentile	0.9±0.01	0.9±0.01	1.0±0.01	1.0±0.01	0.8±0.01	0.9±0.01	0.9±0.01
	Mean change (mm)	-23.4±1.82	-33.9±2.93	-14.5±2.49	-13.3±4.98	-98.3±6.44	-48.65±3.27	-108.1±7.87
Dry days	$\Delta P$ mean	1.2±0.01	1.3±0.02	1.2±0.01	1.1±0.04	1.5±0.02	1.4±0.01	1.6±0.01
	Mean change (days)	2.0±0.13	3.6±0.25	2.1±0.08	1.0±0.31	5.9±0.28	4.1±0.13	6.5±0.11
	$\Delta P$ 90th percentile	1.4±0.03	1.9±0.07	1.5±0.04	1.4±0.10	2.6±0.11	1.8±0.03	2.5±0.06
	Mean change (days)	2.0±0.20	3.6±0.28	2.0±0.16	0.9±0.36	5.7±0.35	3.8±0.16	6.0±0.18
First decile	$\Delta P$ mean	1.0±0.01	1.0±0.01	1.0 ±0.01	1.1±0.02	1.1±0.02	1.0 ±0.01	1.2±0.02
total rain	Mean change (mm)	0.1±0.03	<i>0.1±0.06</i>	-0.1±0.03	0.5±0.18	0.7±0.13	0.2±0.06	1.0±0.12
Tenth decile	$\Delta P$ mean	0.9±0.01	0.9±0.01	1.0 ±0.01	1.0±0.02	0.8 ±0.02	0.9±0.01	0.8±0.02
total rain	Mean change (mm)	-12.1±0.97	-10.9±1.33	<i>1.2±2.00</i>	<i>-1.8±2.17</i>	-44.4±3.72	-25.7±2.44	-52.5±5.75
Tenth decile	$\Delta P$ mean	1.0±0.01	1.1±0.01	1.1±0.01	1.0±0.01	1.0 ±0.01	1.0±0.01	1.1±0.02
rain per day	Mean change (mm/day)	0.4±0.04	0.9±0.03	0.9±0.13	0.1±0.03	0.3±0.07	0.5±0.09	0.6±0.09
n.days	$\Delta P$ mean	0.8±0.01	0.8±0.01	0.8±0.01	0.8±0.02	0.7±0.02	0.8 ±0.01	0.6±0.01
	Mean change (days)	-0.6±0.04	-0.9±0.09	-0.6±0.04	-1.9±0.46	-2.6±0.21	-1.1 ±0.13	-4.9±0.29
intens	$\Delta P$ mean	1.0±0.01	1.1±0.01	1.1±0.01	1.0±0.02	1.1 ±0.02	1.1 ±0.01	1.1±0.02
	Mean change (mm/day)	0.4±0.12	0.9±0.10	2.2±0.20	0.1±0.04	0.7±0.14	1.3 ±0.21	1.4±0.2

598 **LIST OF FIGURES**

599 **Fig. 1.** Top row: 1960–2007 mean (left) and maximum (right) number of stations per square-degree  
600 grid cell from which the APHRODITE observation data is constructed. Centre: China di-  
601 vided into climatologically similar regions. For verification we exclude areas of China with  
602 very low observation station density and very little total monsoon rainfall. Bottom rows:  
603 Precipitation intensity distribution (from area daily mean) for regions in China, climatology  
604 for 1960–2000 - the contribution of daily rainfall total to the total monsoon rainfall, black  
605 line is observations, red and green are ALL and NAT model experiments respectively (the  
606 green line is often hidden behind the red in these plots). . . . . 31

607 **Fig. 2.** Top 4 rows: 1960–2000 mean pentad climatology (5-day total rainfall, mm/5 days) for  
608 observations (centre) and ALL-forcing model ensemble mean (left), and model mean when  
609 normalized to the observed average (right). Second from bottom: Seasonal mean total rain  
610 (mm) for monsoon season for mean of 1960–2000. Bottom row: Maximum daily total rain  
611 (mm) for monsoon season, mean of 1960–2000. . . . . 32

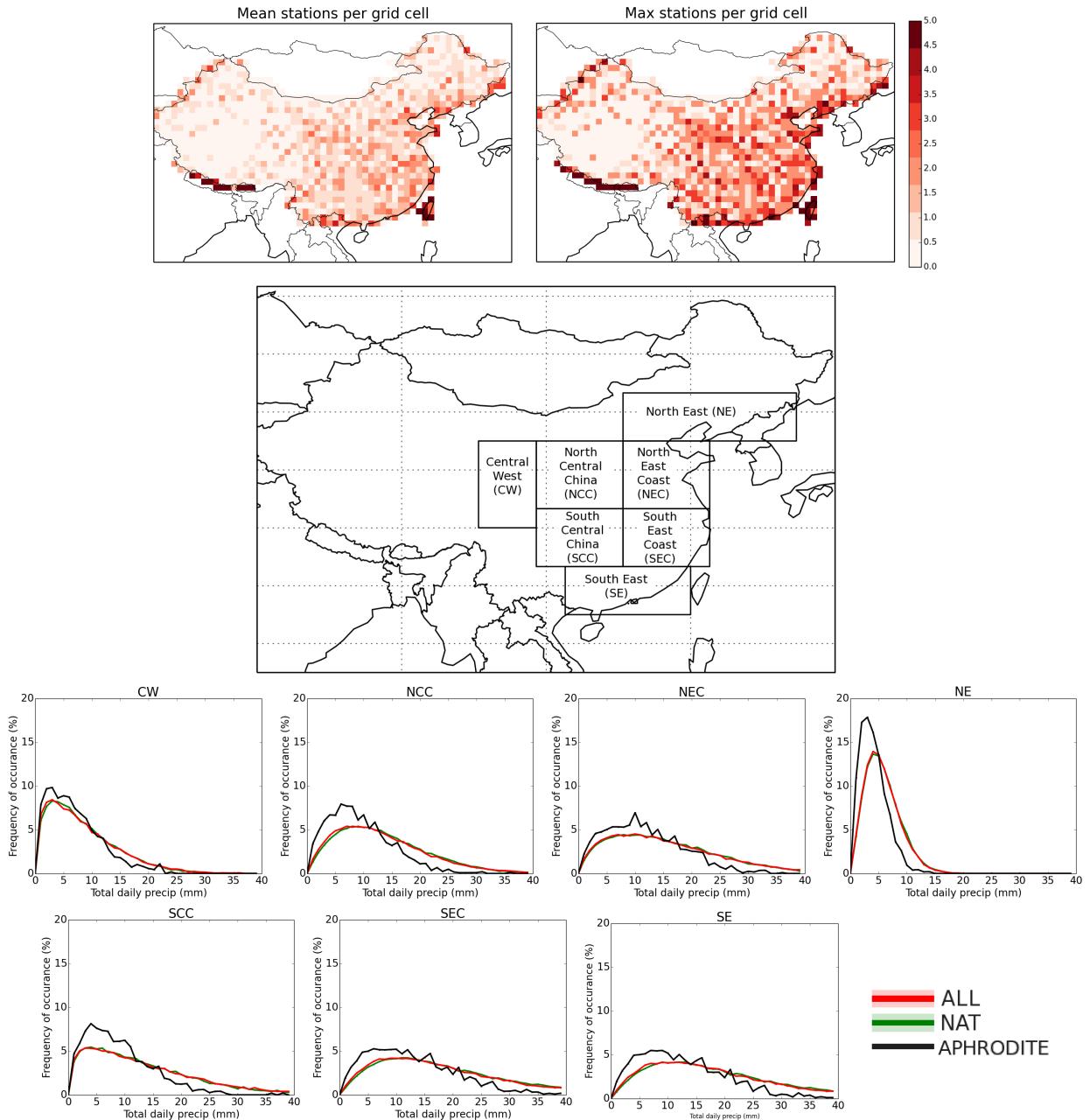
612 **Fig. 3.** 5-day total rainfall time series throughout the monsoon season, averaged over 1960–2000.  
613 Regions corresponding to Figure 1 are indicated above panels. Red and green lines are all-  
614 forcings and natural-forcings ensemble means, red and green shading are ensemble range  
615 (appears brown where the two overlap). Black line is the observations. . . . . 33

616 **Fig. 4.** 5-day total rainfall time series throughout the monsoon season, averaged over 1960–2000.  
617 Blue line shows data for an individual station, indicated in the map with a blue dot. Black  
618 line is APHRODITE. Red and green lines are all-forcings and natural-forcings ensemble  
619 means. The APHRODITE, ALL and NAT are for the individual grid cell in which the  
620 station lies. . . . . 34

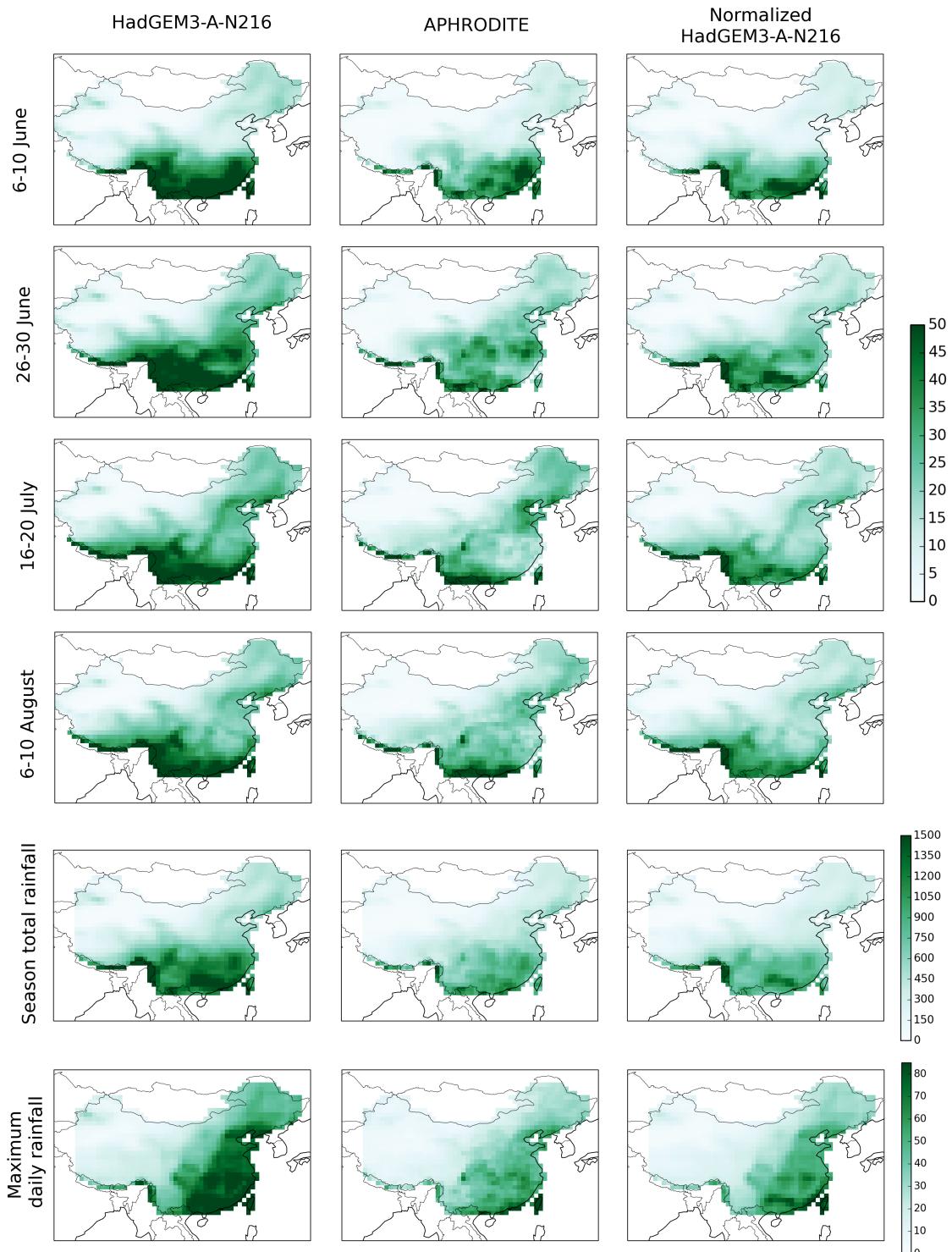
621 **Fig. 5.** Top row: time series for SEC of monsoon season total rainfall (left, anomaly with respect  
622 to 1960–1979) and total dry days during the monsoon (right). Colours as Fig 3. Middle:  
623 Histograms with fitted PDFs for the most recent 20 years of the time series (1996–2015)  
624 for ALL and NAT, black line indicates the mean of the NAT model, dashed line indicates  
625 the mean of ALL model, dot-dashed line indicates 10th and 90th percentile of NAT model  
626 for total rainfall and days below 1 mm respectively. Bottom: Probability ratio ( $\Delta P$ ) maps  
627 between ALL and NAT models, with respect to the mean of the NAT model for all ensemble  
628 members between 1996–2015. Black crosses indicate grid cell where  $\Delta P$  is not significant at  
629 a  $2\sigma$  (95 percent) level. . . . . 35

630 **Fig. 6.** Top: Fractional total rainfall change for 1996–2015 compared to 1960–1979 for each decile  
631 of daily rainfall for SEC. Left column:  $\Delta P$  maps for 1st decile total rain (top), 10th decile  
632 total rain (middle) and 10th decile rain per day (bottom), with respect to the mean of the  
633 NAT model for all ensemble members between 1996–2015. Black crosses indicate grid cell  
634 where  $\Delta P$  is not significant at a  $2\sigma$  (95 percent) level. Right column: Histograms for the  
635 variables in the maps shown for SEC. Solid line indicates the mean of NAT, dashed line  
636 indicates the mean of ALL. . . . . 36

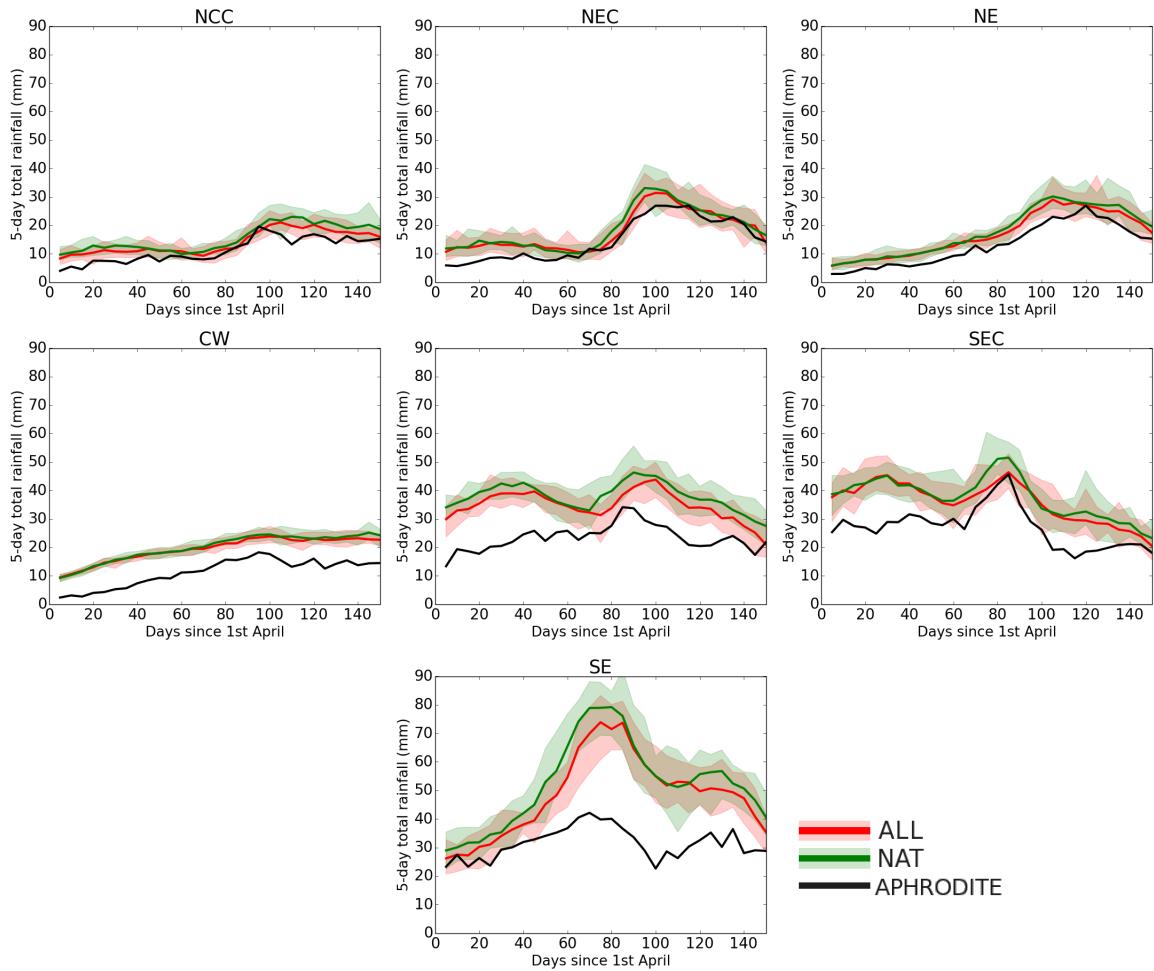
637 **Fig. 7.** Top: time series of intens (left, mm/day) and n\_days (right) for 95th percentile n\_day\_tot  
638 events for SEC. Middle: Histograms with fitted PDFs for variables examined for all events  
639 between 1996–2015 in ALL and NAT. Bottom:  $\Delta P$  maps, with respect to the mean of the  
640 NAT model, for all ensemble members between 1996–2015, for events in the 95th percentile  
641 (w.r.t. 1960–1979) of n\_day\_tot. Black crosses indicate grid cells where  $\Delta P$  is not significant  
642 at a  $2\sigma$  (95 percent) level. . . . . 37



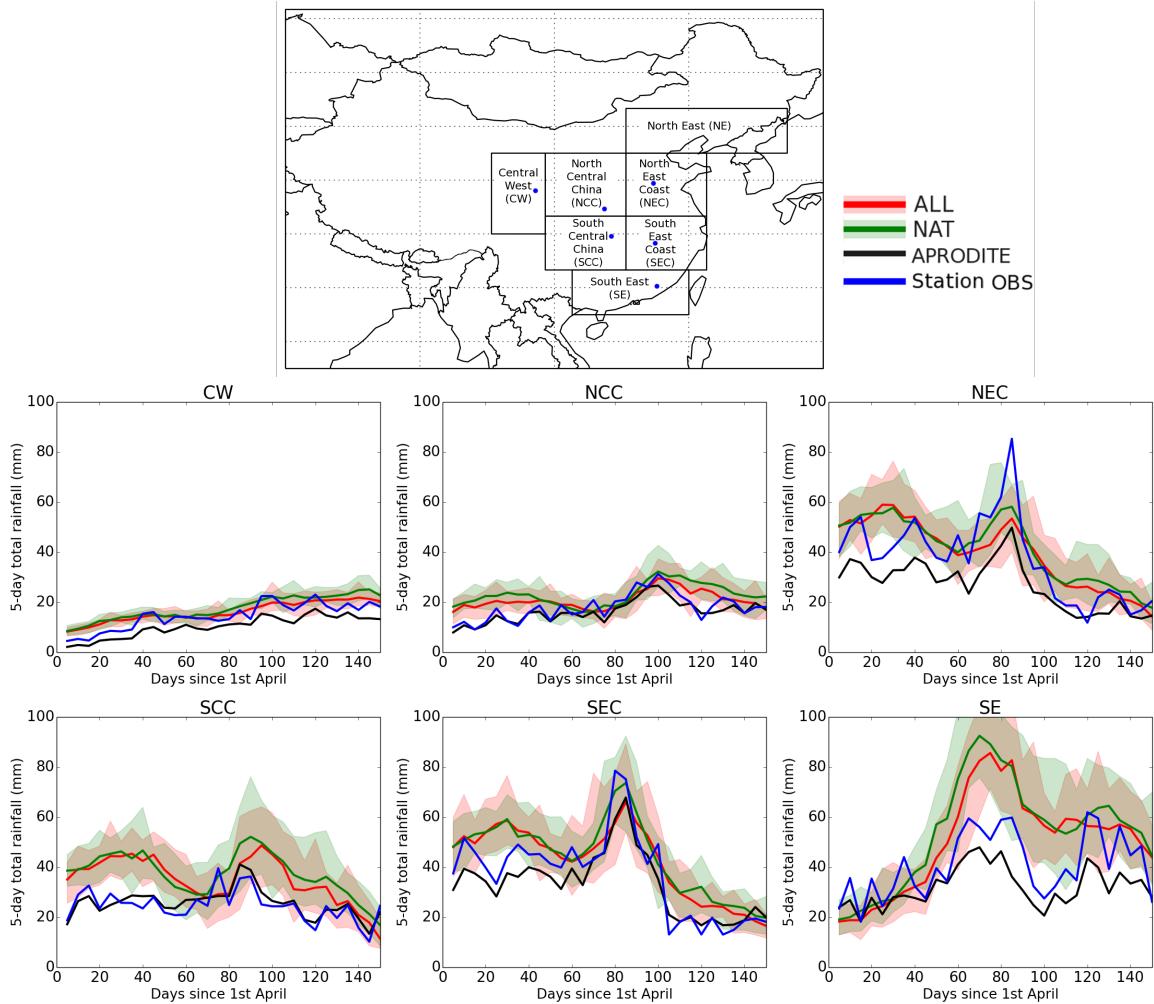
643 FIG. 1. Top row: 1960–2007 mean (left) and maximum (right) number of stations per square-degree grid  
 644 cell from which the APHRODITE observation data is constructed. Centre: China divided into climatologically  
 645 similar regions. For verification we exclude areas of China with very low observation station density and very  
 646 little total monsoon rainfall. Bottom rows: Precipitation intensity distribution (from area daily mean) for regions  
 647 in China, climatology for 1960-2000 - the contribution of daily rainfall total to the total monsoon rainfall, black  
 648 line is observations, red and green are ALL and NAT experiments respectively (the green line is often hidden  
 649 behind the red in these plots).



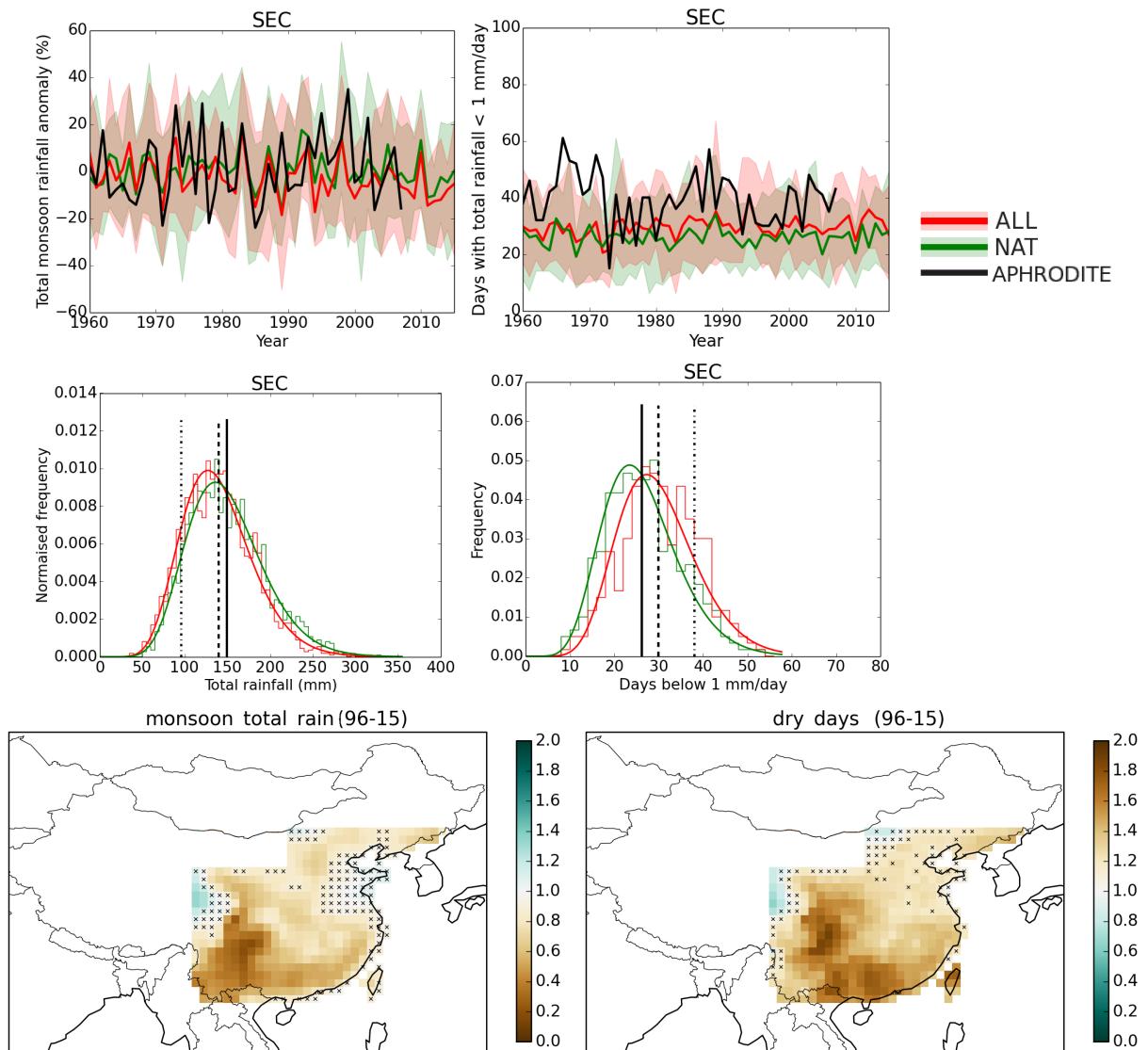
650 FIG. 2. Top 4 rows: 1960–2000 mean pentad climatology (5-day total rainfall, mm/5 days) for observations  
 651 (centre) and ALL-forcing ensemble mean (left), and model mean when normalized to the observed average  
 652 (right). Second from bottom: Seasonal mean total rain (mm) for monsoon season for mean of 1960-2000.  
 653 Bottom row: Maximum daily total rain (mm) for monsoon season, mean of 1960-2000.



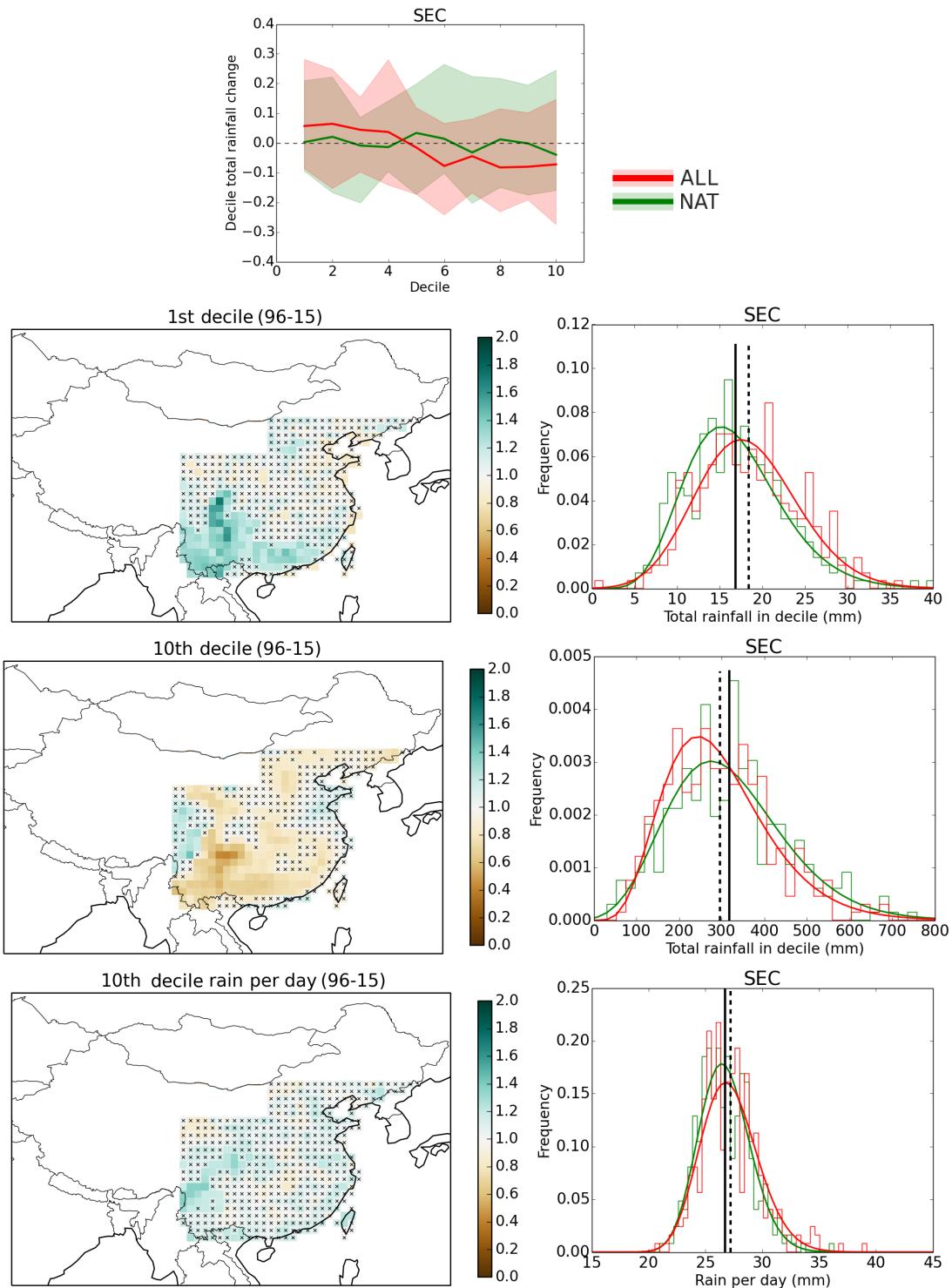
654 FIG. 3. 5-day total rainfall time series throughout the monsoon season, averaged over 1960–2000. Regions  
 655 corresponding to Figure 1 are indicated above panels. Red and green lines are ALL-forcings and NAT-forcings  
 656 ensemble means, red and green shading are ensemble range (appears brown where the two overlap). Black line  
 657 is the observations.



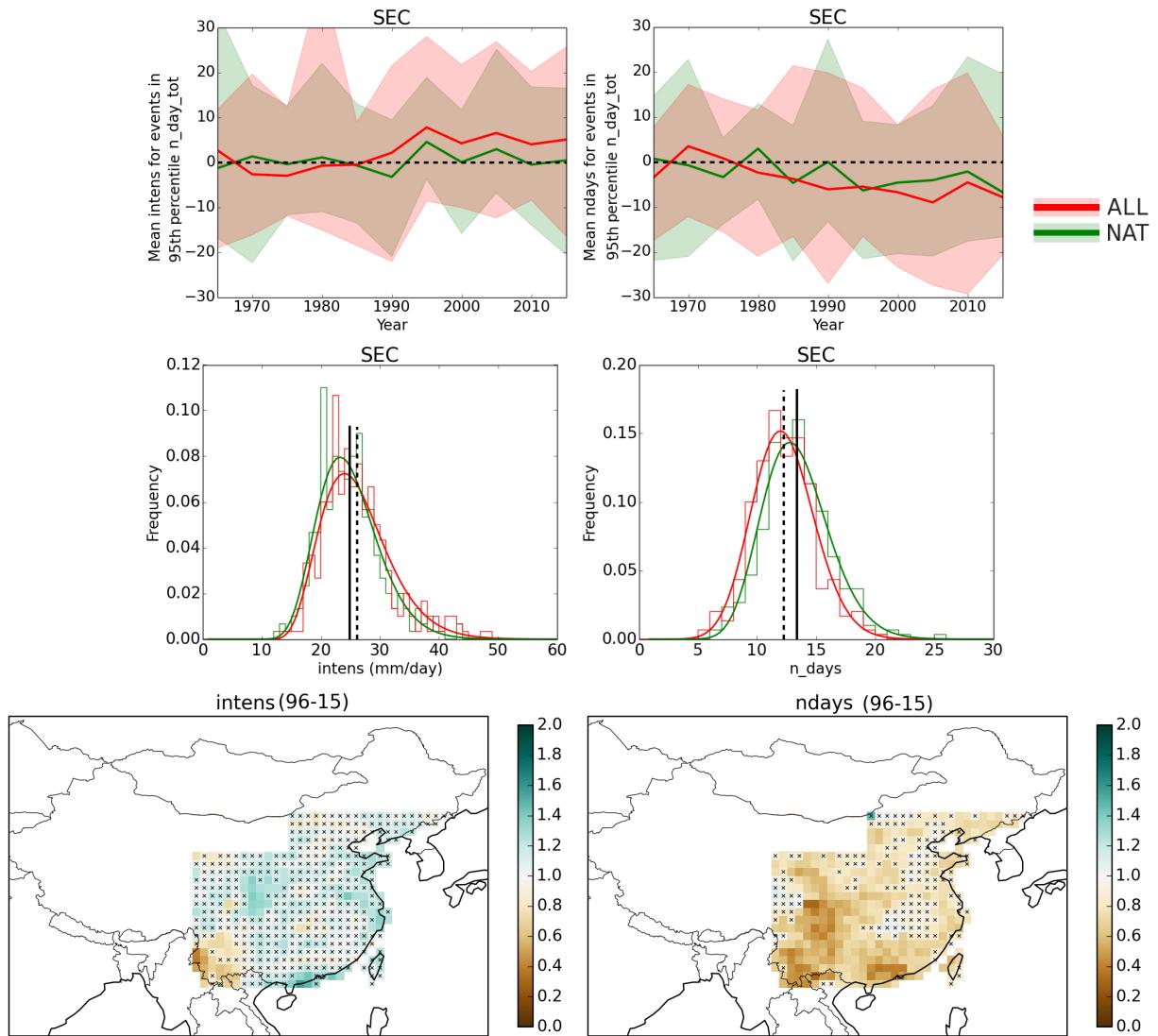
658 FIG. 4. 5-day total rainfall time series throughout the monsoon season, averaged over 1960–2000. Blue line  
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 660 green lines are ALL-forcings and NAT-forcings ensemble means. The APHRODITE, ALL and NAT are for the  
 661 individual grid cell in which the station lies.



662 FIG. 5. Top row: time series for SEC of monsoon season total rainfall (left, anomaly with respect to 1960-  
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 667 ( $\Delta P$ ) maps between ALL and NAT ensembles, with respect to the mean of the NAT ensemble for all ensemble  
 668 members between 1996-2015. Black crosses indicate grid cell where  $\Delta P$  is not significant at a  $2\sigma$  (95 percent)  
 669 level.



670 FIG. 6. Top: Fractional total rainfall change for 1996-2015 compared to 1960-1979 for each decile of daily  
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 672 decile rain per day (bottom), with respect to the mean of the NAT ensemble for all ensemble members between  
 673 1996-2015. Black crosses indicate grid cell where  $\Delta P$  is not significant at a  $2\sigma$  (95 percent) level. Right column:  
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676 FIG. 7. Top: time series of intens (left, mm/day) and n\_days (right) for 95th percentile n\_day\_tot events for  
 677 SEC. Middle: Histograms with fitted PDFs for variables examined for all events between 1996-2015 in ALL and  
 678 NAT. Bottom:  $\Delta P$  maps, with respect to the mean of the NAT ensemble, for all ensemble members between  
 679 1996-2015, for events in the 95th percentile (w.r.t. 1960-1979) of n\_day\_tot. Black crosses indicate grid cells  
 680 where  $\Delta P$  is not significant at a  $2\sigma$  (95 percent) level.