

**A modified regional L-moment method for regional extreme
precipitation frequency analysis in the Songliao River Basin of China**

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63 1 Abstract
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65 2 The regional frequency analysis (RFA) is a widely used method in analyzing the
66 3 changes of extreme precipitation (EP). The uncertainties in the identification of
67 4 homogeneous subregions and the selection of optimal regional frequency distributions
68 5 can largely influence the results of the RFA. In this study, the fuzzy c-means method
69 6 combined with the extended Xie-Benn index (FCXB) is used to help determine the
70 7 optimal division of subregions. In addition, we introduce a new comprehensive index
71 8 (CI) to overcome the shortcomings of present measures and reduce the uncertainty in
72 9 regional frequency distribution selection. The changes of EP at 93 meteorological
73 10 stations in the Songliao River Basin (SRB) during 1960 to 2016 is analyzed. The main
74 11 results show that: (1) FCXB can effectively identify the optimum number of
75 12 homogeneous subregions automatically, and the corresponding subregion division is
76 13 proven to be reasonable and reliable; (2) compared with the single goodness-of-fit
77 14 measure, the developed CI can reduce the uncertainties in distribution selection and
78 15 determine the optimal regional distribution in a reliable way; (3) the estimated EP under
79 16 different return periods both decrease from the south to the north of the SRB, which
80 17 indicates the risk of high-intensity EP events in the southern SRB is relatively higher.
81 18 These findings can provide technical support for local policymakers to formulate
82 19 effective measures to lessen the damages of the EP on ecosystem and society.

83 20 **Keywords:** regional frequency analysis; L-moments method; a comprehensive index;
84 21 Xie-Benn index; the Songliao River Basin

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122 **1 Introduction**
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125 23 According to the fifth IPCC report (2013), the frequency of extreme precipitation
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127 24 (EP) events has significantly increased in many land regions since the 1950s, causing
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130 25 huge economic losses (Jun et al., 2017; Su et al., 2008). Moreover, the increasing trend
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132 26 of EP is projected to continue in the 21st century in many regions across the world,
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134 27 especially in the high latitudes and tropical regions (Alexander and Arblaster, 2009;
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137 28 Hao et al., 2013). The frequent occurrence of EP, which is mainly attributed to climate
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140 29 change and human activities (Konisky et al., 2016; Tao et al., 2011), can probably alter
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142 30 the balance of local ecosystem, and will likely trigger other natural hazards such as
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145 31 floods (Ashfaq et al., 2010; Mishra et al., 2012), drought (Mukherjee et al., 2018), and
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147 32 landslides (Wu et al., 2017). Therefore, understanding the changes in EP (frequency,
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150 33 trends, etc.) is of great significance and can help water resources managers formulate
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152 34 effective adaptation strategies to minimize catastrophic losses.
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155 35 Basically, there are two ways to carry out an EP frequency analysis: the at site
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157 36 frequency analysis (ASF) method and the regional frequency analysis (RFA) method
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160 37 (Hosking and Wallis, 1997). Compared to the ASF method, which cannot be applied at
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162 38 ungauged stations, the main advantage of the RFA method is that it can use data from
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165 39 multiple gauged stations to predict the meteorological characteristics in an ungauged
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167 40 region (Cunnane, 1988; She et al., 2014). The most well-known RFA method is the
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170 41 regional L-moment method (denoted as LM), which has been widely used in the RFA
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172 42 of EP in many regions around the world (Chen et al., 2014; Fowler and Kilsby, 2003;
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181 43 Ngongondo et al., 2011; Yang et al., 2010a). Generally, the procedure of LM consists
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183 44 of five steps: (a) identification of homogeneous subregions; (b) screening of the data
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186 45 using discordancy measures; (c) the homogeneity test using heterogeneous measures;
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189 46 (d) selection of the optimal regional distributions; and (e) quantiles estimation and
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191 47 accuracy assessment.

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193 48 Determining the number of subregions plays an important role in the work of LM
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195 49 since an inappropriate number of subregions will lead to an unreasonable division
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198 50 pattern that may not satisfy the homogeneity assumption of the RFA (Forestieri et al.,
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201 51 2018; Rao and Srinivas, 2006). Many previous studies determined the number of
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204 52 subregions by setting an initial number based on the regional geographical
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207 53 characteristics and then adjusting the number back and forth until all divided subregions
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209 54 could pass the homogeneity test (Du et al., 2014; Yang et al., 2010b). However, such
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211 55 an approach is subjective, and the determined number of subregions may not be the
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214 56 most appropriate. Some objective cluster methods such as the K-means method and the
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217 57 fuzzy c-means method (denoted as FC) with some cluster validity indices have also
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219 58 been employed for determining the optimum number of subregions in some studies
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221 59 (Forestieri et al., 2018; Halkidi et al., 2001). However, selecting a reliable cluster
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224 60 validity index is important for the determination of the optimum subregion number as
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227 61 different indices usually lead to different results. In this study, the FC with a reliable
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229 62 index, the extended Xie-Benn index (denoted as FCXB), is employed to identify the
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231 63 homogeneous subregions (Basu and Srinivas, 2015; Rao and Srinivas, 2006; Xie and
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240 64 Beni, 1991). As confirmed by Xie and Beni (1991) and Hamerly and Elkan (2002),
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242 65 FCXB performs better than the K-means method in producing hard clustering solutions.
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245 66 In addition, the FCXB presents a direct connection to the properties of the input data so
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248 67 that the results of the FCXB do not exhibit monotonic increasing or decreasing trends
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250 68 with the increase in the subregion number. However, the connection to the input data
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252 69 is lacking in some other validity indices (such as the fuzzy partition coefficient or the
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255 70 fuzzy partition entropy), which will lead to the monotonic trends in their results and
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258 71 unreasonable decisions for the subregion number (Halkidi et al., 2001; Hall and Minns,
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260 72 1999).

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262 73 The determination of an appropriate regional frequency distributions is also
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264 74 important in the RFA. An inappropriate selection of distributions may result in a large
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267 75 overestimation or underestimation of the risk of EP. Several goodness-of-fit measures
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270 76 have been proposed to select the optimal regional distribution, and the goodness-of-fit
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273 77 measure proposed by Hosking and Wallis (1997) (denoted as HWGOF) and the
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275 78 graphical measure using the L-diagram (denoted as GMLM) (Peel et al., 2001; Vogel
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278 79 et al., 1993) are the two most widely used. However, the results of GMLM may not be
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280 80 reliable because the selection of the optimal regional distributions mainly depends on
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283 81 subjective judgments. In addition, Kjeldsen and Prosdocimi (2015) claimed that the
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285 82 distributions suggested by the HWGOF are not robust enough due to the inadequate
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288 83 consideration of the variability of the L-skewness, and they proposed a new bivariate
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290 84 extension goodness-of-fit measure (denoted as KPGOF), which considers the
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299 85 variability of both the L-skewness and L-kurtosis as well as their correlation. The
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301 86 KPGOF can improve the ability and stability in selecting the true population
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304 87 distribution in most situations except when the true distribution is a generalized logistic
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307 88 distribution (Kjeldsen et al., 2017; Kjeldsen and Prosdocimi, 2015). In this study, we
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309 89 will first compare the efficiency of the HWGOF, GMLM, and KPGOF in determining
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311 90 the optimal regional distribution and then develop a comprehensive index (denoted as
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314 91 CI) based on the joint consideration of the three previously described measures. We
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317 92 aim to provide a more reliable way based on CI to help choose the most appropriate
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320 93 regional distributions, especially when the results of HWGOF, GMLM, and KPGOF
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322 94 are inconsistent.

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324 95 In this study, the Songliao River Basin (SRB) is selected as the study area, and the
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327 96 RFA of the EP in this region is investigated through the LM with FCXB and CI. The
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330 97 objectives of this study are to (1) reduce the uncertainty in the identification of the
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332 98 homogeneous subregions through applying the FCXB to determine the optimum
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334 99 number of subregions and the corresponding division of homogeneous subregions and
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100 (2) construct a comprehensive index with the joint considerations of three different
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101 goodness-of-fit measures to determine the optimal regional distribution in a more
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102 reliable way.

103 **2 Study area and methodology**

104 **2.1 Study area and data**

105 The Songliao River Basin (115°31'E–135°9'E, 38°35'N–53°35'N) is one of the most

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358 106 important agricultural and industrial regions in northeastern China (Liang et al., 2011;
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360 107 Song et al., 2014). However, the frequency of EP in the SRB has been largely increased
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363 108 in recent years, causing significant economic losses and huge damage to local
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366 109 infrastructures (Ma et al., 2004; Wang et al., 2013). Thus, it is of great necessity to
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369 110 assess the EP over the whole SRB. The SRB covers a drainage area of approximately
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371 111 1.24×10^6 km², including the northeast of the Inner Mongolia province, Liaoning
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373 112 province, Jilin province, and Heilongjiang province. The Amur River, Liao River, Yalu
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376 113 River, Tumen River, Suifen River, Daling River, and Ergun River are the seven major
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379 114 rivers in the SRB. Of these seven rivers, the largest is the Amur River, with a length of
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381 115 approximately 4440 km and a drainage area of approximately 8.88×10^5 km² in the
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384 116 territory of China. The largest tributary of the Amur River in China is the Songhua
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386 117 River, with a length of 1927 km and a drainage area of 5.568×10^5 km², which is formed
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389 118 by the confluence of the southern Second Songhua River tributary and the Northern
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391 119 Nenjiang River tributary (Song et al., 2015). The SRB belongs to temperate and cold
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394 120 temperate zones and has a continental monsoon climate. The long-term annual mean
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396 121 precipitation (denoted as LAMP) of the SRB shows a south-north gradient, varying
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399 122 from more than 1000 mm in the southern SRB to less than 350 mm on the northern
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401 123 edge of the SRB (Qi, 2006). The east, west, and north of the SRB are surrounded by
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404 124 mountains, and the highest mountain with an elevation of 2439 m is located in the west
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406 125 of the SRB. The long-term annual mean air temperature varies from 1°C to 5°C, and
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408 126 the annual range of air temperature can reach up to 40°C. Fig. 1 shows the location and
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417 127 the geographic information of the study area.
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419 128 In this study, the daily precipitation observations (from 1960 to 2016 without gaps)
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422 129 of 93 national meteorological stations in the SRB are used. These data were obtained
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425 130 from the National Meteorological Administration of China (<http://data.cma.cn/>), which
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427 131 is the official institute of China providing high-quality meteorological data. The
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430 132 specific locations of the 93 stations in SRB are given in Fig. 1. In this study, the EP
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432 133 time series at each station is obtained as the annual maximum daily precipitation
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435 134 (denoted as AMP, mm) derived from the daily rainfall observations.
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437 135 **2.2 Methodology**

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439 136 In this study, the LM with FCXB and CI is applied for the RFA of the EP in the SRB.
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442 137 More details about the LM can be found in the study by Hosking and Wallis (1997).
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445 138 The major steps of the LM are briefly introduced below.

446 139 **2.2.1 The identification and delineation of homogeneous subregions**

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448 140 FCXB is employed in this study for the identification of the homogeneous subregions,
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451 141 as it can determine the optimum number of subregions automatically in a reliable way.
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454 142 The procedure of FCXB consists of three parts: First, select and use several
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456 143 geographical or meteorological characteristics (such as longitude, LAMP, etc.,) of all
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459 144 stations to form the input data matrix. Second, apply the input data matrix to calculate
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461 145 the partition membership matrixes with different numbers of subregions; more details
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464 146 on the process of obtaining the partition membership matrix are provided in the study
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466 147 by Rao and Srinivas (2006). Finally, based on these partition membership matrixes, the
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469 148 values of the extended Xie-Benn index corresponding to different numbers of
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476 subregions can be computed as:
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$$478 \quad 150 \quad V_{XB} = (\sum_{j=1}^c \sum_{k=1}^K (\mu_{jk})^r \|V_j - W_k\|^2) / (K \min_{j,j \neq k} \|V_j - V_k\|^2) \quad (1)$$

481 where μ_{jk} denotes the member of partition membership matrix U at row j and column
482 k . K and c denote the numbers of column and row of U , respectively. W_k denotes the
483 vector of input data matrix W at row k . V_j denotes a fuzzy centroid vector that can be
484 calculated as $V_j = \sum_{k=1}^K (\mu_{jk})^r W_k / \sum_{k=1}^K (\mu_{jk})^r$, where r denotes the fuzzifier, which
485 controls the extent of membership shared among fuzzy clusters. For most data sets,
486 $1.25 \leq r \leq 2.5$ gives good results for FC (Srinivas et al., 2008; Zhang and Hall, 2004).
487

488 The minimum V_{XB} indicates the optimum number of compact and well-separated
489 subregions. After determining the optimum number of subregions and the
490 corresponding partition membership matrix, each station can be assigned to a specific
491 subregion according to its maximum membership in the partition membership matrix.
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493 161 **2.2.2 Screening of data using the discordancy measure**

494 Assume that there are N stations in the study region, let $t^{(i)}, t_3^{(i)}, t_4^{(i)}$ denote the
495 coefficient of variation (L-CV), L-skewness, and L-kurtosis at station i , respectively,
496 and $u_i = [t^{(i)}, t_3^{(i)}, t_4^{(i)}]^T$. The discordancy measure for station i , D_i , can be calculated
497 as:
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$$499 \quad 166 \quad D_i = N (u_i - \bar{u})^T S^{-1} (u_i - \bar{u}) / 3 \quad (2)$$

500 where $u_i = [t^{(i)}, t_3^{(i)}, t_4^{(i)}]^T$, $\bar{u} = \sum_{i=1}^N u_i / N$ and $S = \sum_{i=1}^N (u_i - \bar{u})(u_i - \bar{u})^T$ (Neykov et al., 2007). The
501 stations with D_i values larger than the critical value that is related to the number of
502 sites in the study region are considered to be discordant with the other stations.
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535 170 **2.2.3 Testing of regional homogeneity using the heterogeneity measure**

536 171 Three heterogeneity measures (H), namely H_1 , H_2 , and H_3 , are used to examine the
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539 172 assumption of the RFA that each divided subregion is a homogeneous region (She et
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541 173 al., 2014). H_1 , H_2 , and H_3 can be calculated as:

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$$H_1 = (V_1 - \mu_v) / \sigma_v, H_2 = (V_2 - \mu_{v2}) / \sigma_{v2}, H_3 = (V_3 - \mu_{v3}) / \sigma_{v3} \quad (3)$$

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546 175 where V_1 , V_2 , and V_3 are the weighted standard deviations of the at-site sample L-
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549 176 moment ratios that can be calculated as:

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$$\begin{cases} V_1 = \left[\frac{\sum_{i=1}^N n_i (t^{(i)} - t^R)^2}{\sum_{i=1}^N n_i} \right]^{1/2} \\ V_2 = \frac{\sum_{i=1}^N n_i \left[(t^{(i)} - t^R)^2 + (t_3^{(i)} - t_3^R)^2 \right]}{\sum_{i=1}^N n_i}^{1/2} \\ V_3 = \frac{\sum_{i=1}^N n_i \left[(t_3^{(i)} - t_3^R)^2 + (t_4^{(i)} - t_4^R)^2 \right]}{\sum_{i=1}^N n_i}^{1/2} \end{cases} \quad (4)$$

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560 178 where n_i denotes the recording length at station i and t^R , t_3^R , and t_4^R denote the
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562 179 regional average L-moments ratios ($t_j^R = \frac{\sum_{i=1}^N n_i t_j^{(i)}}{\sum_{i=1}^N n_i}$, $j = 1, 3, 4$) (Yang et al., 2010a).

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565 180 μ and σ are the mean and standard deviation of V derived from a large number (
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568 181 N_m), which is set as 500 here, of simulated realizations of the study region by Monte
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570 182 Carlo simulation. Each simulated realization contains N stations with the same record
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573 183 length as their real-world counterpart and has a four parameter Kappa distribution fitted
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575 184 by the regional average L-moments ratios ($1, t^R, t_3^R, t_4^R$) as the frequency distribution.

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578 185 More details about Kappa distribution can be found in the study by Kjeldsen et al.
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580 186 (2017). The study region can be regarded as being “acceptably homogeneous” if
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583 187 $H_i < 1 (i = 1, 2, 3)$, “possibly homogeneous” if $1 \leq H_i < 2 (i = 1, 2, 3)$ and “definitely
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585 188 heterogeneous” if $H_i \geq 2 (i = 1, 2, 3)$.

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593 **189 2.2.4 Choice of optimal regional frequency distribution**
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595 190 In this study, four candidate probability distributions that are frequently used in the
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597 191 LM, i.e., the Pearson-III distribution (denoted as PE3), generalized normal distribution
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599 192 (denoted as GNO), generalized logistic distribution (denoted as GLO), and generalized
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601 193 extreme value distribution (denoted as GEV), are considered (Fowler and Kilsby, 2003;
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603 194 Yang et al., 2010a). More detail about these frequency distributions can be seen in the
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605 195 study by Hosking and Wallis (1997). Three measures (HWGOF, GMLM, KPGOF) and
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607 196 a newly constructed comprehensive index CI will be separately introduced below.
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613 **197 2.2.4.1 HWGOF**
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615 198 HWGOF (Z^{DIST}), using the L-kurtosis for the distribution selection (Hosking and
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617 199 Wallis, 1997), can be calculated for each candidate distribution as:

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$$Z^{DIST} = (\tau_4^{DIST} - t_4^R + \beta_4) / \sigma_4 \quad (5)$$

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623 201 where τ_4^{DIST} is the L-kurtosis of the fitted candidate distribution to the data. β_4 and
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625 202 σ_4 denote the bias and standard deviation of t_4^R , respectively, which can be computed
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627 203 as:

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$$\beta_4 = \sum_{m=1}^{N_m} (t_4^{(m)} - t_4^R) / N_m \quad (6)$$

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$$\sigma_4 = \left\{ \frac{1}{N_m - 1} \left[\sum_{m=1}^{N_m} (t_4^{(m)} - t_4^R)^2 - N_m \beta_4^2 \right] \right\}^{1/2} \quad (7)$$

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637 206 where $t_4^{(m)}$ denotes the sample regional L-kurtosis derived from the m th simulation. If
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639 207 $|Z^{DIST}| \leq 1.64$, the candidate distribution can be considered acceptable. The distribution
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641 208 with the minimum $|Z^{DIST}|$ among all the acceptable distributions is the best regional
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643 209 distribution.
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653 210 2.2.4.2 GMLM
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655 211 GMLM is a widely-used graphical measure based on L-diagrams, which is a simple
656 212 but useful visual comparison method. With the verification of several studies (Kjeldsen
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658 212 and Prosdocimi, 2015; Vogel et al., 1993; Vogel and Wilson, 1996), the distribution
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660 213 whose theoretical curve is the closest to the regional mean L-moment ratios point can
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662 214 be suggested to be the most appropriate regional distribution.
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668 216 2.2.4.3 KPGOF
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671 217 The procedure of KPGOF consists of two steps (Kjeldsen and Prosdocimi, 2015):
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673 218 first, using the L-diagrams with the $(1-\alpha)100\%$ confidence ellipse, where α is the
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675 219 given significance level, to determine the acceptable distributions. The distributions
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677 220 whose theoretical curves are located within the area of the ellipse are considered as
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679 221 acceptable distributions. Second, for each acceptable distribution, D^{DIST} can be
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681 222 calculated as:
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686 223
$$D^{DIST} = (\tau^{DIST} - t^R)^T \Omega^{-1} (\tau^{DIST} - t^R) \quad (8)$$

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688 224 where $t_B^R = (t_3^R - \beta_3, t_4^R - \beta_4)$ denotes the vector of the bias-corrected regional L-
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690 225 skewness and L-kurtosis. Ω is a covariance matrix as $\begin{bmatrix} \sigma_3^2 & \sigma_{34} \\ \sigma_{43} & \sigma_4^2 \end{bmatrix}$, where σ_{34} is the
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692 226 covariance between the L-skewness and L-kurtosis, which can be estimated as:
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697 227
$$\sigma_{34} = (N_m - 1)^{-1} \left\{ \sum_{m=1}^{N_m} (t_3^{(m)} - t_3^R)(t_4^{(m)} - t_4^R) - N_m \beta_3 \beta_4 \right\} \quad (9)$$

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700 228 where $t_3^{(m)}$ is the regional average L-skewness derived from the m th simulation. β_3
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702 229 and σ_3 denote the bias and standard deviation of t_3^R , respectively. If $|D^{DIST}| \leq 4.61$,
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704 230 the candidate distribution can be viewed as acceptable. The distribution with the
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231 minimum $|D^{DIST}|$ can be accepted as the most appropriate one among all the
 232 acceptable distributions.

233 2.2.4.4 CI

234 The CI is constructed based on the results of the three foregoing introduced measures
 235 to help determine the optimal regional distribution, especially when the best
 236 distributions suggested by the three measures are different. The theory of CI is that the
 237 distribution accepted by the majority of goodness-of-fit measures should be considered
 238 as the most appropriate regional distribution. For each candidate distribution, the value
 239 of CI (T^{DIST}) can be calculated as:

$$240 \begin{cases} T^{DIST} = A * D^{DIST} / D^{Th} + B * |Z^{DIST}| / Z^{Th} + C * G^{DIST} \\ A+B+C = 1 \end{cases} \quad (10)$$

241 where the values of G^{DIST} are set as 0 for all possible optimal distributions suggested
 242 by GMLM and 1 for the other distributions. D^{Th} and Z^{Th} denote the critical values of
 243 KPGOF and HWGOF, which are set as 4.61 and 1.64 under the significance level of
 244 5%, respectively. A , B and C are the weights of KPGOF, HWGOF, and GMLM,
 245 respectively. The values of A , B , and C are related to the performance of corresponding
 246 measures, with a smaller value indicating a more robust performance. In this study, the
 247 initial values of weights are all set as 1/3 on the condition that comparisons of the
 248 performance of the three measures have never been conducted for the study region. For
 249 those unacceptable distributions determined by any of the three measures, the values of
 250 T^{DIST} will be set as its upper limit of 1. The distribution with the minimum value of
 251 T^{DIST} is considered the optimal regional distribution.

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771 **252 3 Results and discussions**
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774 **253 3.1 Trend analysis**
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776 254 The Mann Kendall (MK) test (Romanić et al., 2015) is used to examine the trends of
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778 255 the AMP time series at 93 stations in the SRB from 1960 to 2016. A boxplot of the MK
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781 256 test results of 93 sites is given in Fig. 2 (a). The 5% level is used to determine the
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783 257 significance of the trends. It can be seen from Fig. 2 (a) that all the MK statistics are in
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786 258 the range of -1.96–1.96, which means that the AMP time series at the 93 stations do not
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789 259 have significant changes in their trends. The spatial distribution of the MK results of
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791 260 the 93 stations is presented in Fig. 2 (b). It can be found that the AMP time series at 39
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794 261 stations show increasing trends, while the remaining 54 stations show decreasing trends.
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796 262 The AMP time series at the 93 stations can be used for the RFA of the EP without
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799 263 consistency correction, as there are no significant changes in the trends of any of them.
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801 **264 3.2 Identification of homogeneous subregions**
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804 265 In this study, four factors, including the longitude, latitude, elevation, and LAMP of
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806 266 each station in the SRB, are employed in FCXB to obtain the optimal division of the
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809 267 study area, and the result is presented in Fig. 3. We can observe that the values of the
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811 268 extended Xie-Benn index do not present an overall monotonic increasing or decreasing
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814 269 tendency when the subregion number increases. This change pattern is consistent with
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816 270 the results in the study by Rao and Srinivas (2006) and Srinivas et al. (2008). The
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819 271 optimum number of subregions of the SRB can be determined to be six because the
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821 272 extended Xie-Benn index obtains the minimum value under this case (Fig. 3). We depict
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830 273 the boundaries of the six subregions in Fig. 4 and list the stations in each subregion in
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832 274 Tab. 1. Generally, subregion I, with the highest elevation and the lowest LAMP of the
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835 275 entire SRB, is located in the west of the SRB, and the whole Ergun River is located in
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838 276 this subregion. Subregion II mainly represents the central areas of the SRB, which is
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840 277 characterized by a large plain area with a low LAMP of approximately 450 mm. This
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843 278 subregion includes the Nenjiang River and the west of the Liao River. Subregion III
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845 279 with an elevation of less than 500 m, is located in the northeast of the SRB. There is
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848 280 not much precipitation in this subregion, and the LAMP of most areas in this subregion
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850 281 is approximately 550 mm. Most areas with low elevation in the west and the center of
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853 282 Liaoning province are associated with subregion IV, and the LAMP over this subregion
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855 283 is 616 mm, which is larger than that of the three previous subregions. The Daling River
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858 284 and the mainstream of Liao River are both located in this subregion, and the southern
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860 285 part of subregion IV is near Bohai Bay of China. Most of the eastern areas of Liaoning
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863 286 province are located in subregion V. The elevation of subregion V is higher than that
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865 287 of subregion IV, and this subregion has the highest LAMP of the whole SRB, as the
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868 288 LAMP in most areas exceeds 750 mm. Subregion VI contains the high-elevation areas
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870 289 in the southeastern SRB. The LAMP of this subregion is almost the same as that of
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873 290 subregion IV, and both are higher than the LAMPs of subregions I and III.

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875 291 To verify the rationality of the current division of the SRB, we compare it with the
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878 292 previous division pattern in the study by Zhang et al. (2012), which mainly considers
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880 293 the hydrological and geographical characteristics of the SRB. It can be found that these
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889 294 two divisions show a large similarity in the northern SRB but present some discrepancy
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892 295 in the southern SRB with the complicated river system. Such a result shows that the
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894 296 division in this study is not only based on the geographical and hydrological
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897 297 characteristics of the SRB but also on the spatial distribution of the LAMP.

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899 298 To further verify the reliability and robustness of the results of FCXB, we also apply
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902 299 other validity indices, the fuzzy partition coefficient and fuzzy partition entropy, for the
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904 300 determination of the optimum subregions number of the SRB. The values of the two
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907 301 indices present an overall monotonic increasing or decreasing trend with an increase in
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910 302 the subregion number, suggesting an optimum number of two, but the two subregions
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912 303 have been proven by us to not be capable of passing the homogeneity test. This result
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914 304 is similar to the conclusions in some previous studies (Güler and Thyne, 2004; Hamerly
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917 305 and Elkan, 2002; Srinivas et al., 2008). In addition, considering the large spatial extent
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920 306 of the SRB and the spatial variability of the LAMP in the SRB (Zhang et al., 2012), it
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922 307 is inappropriate to divide the whole SRB into only 2 subregions. Thus, our division of
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925 308 subregions can be considered reasonable and reliable for the RFA of the EP in the SRB.
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927 309 The better performance of the extended Xie-Benn index is related to its strong
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930 310 connection with the input data (Rao and Srinivas, 2006; Xie and Beni, 1991).

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932 311 After separating the SRB into 6 subregions, the discordancy measure is used to find
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934 312 the grossly discordant stations in each subregion. The critical values ($D_{critical}$) depend
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937 313 on the number of stations in each subregion, which are 2.632, 3, 2.971, 3, 2.869 and
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940 314 2.971 for subregions I to VI, respectively. The discordancy measure values of all

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948 315 stations are presented in Tab. 1. The results show that the discordancy measure values
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951 316 of all stations are smaller than the regional critical values, which means that all the
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954 317 stations in the SRB have passed the discordancy test.

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956 318 Then, the homogeneity of each subregion is tested using three heterogeneity
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959 319 measures (H_1 , H_2 , and H_3), and the results are shown in Tab. 1. It is obvious that the
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961 320 values of the three heterogeneity measures H_1 , H_2 , and H_3 for the six subregions are less
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964 321 than 1, which demonstrates that all subregions without subjective adjustments can be
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966 322 accepted as homogeneous regions. The results of our study are consistent with the
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969 323 conclusion drawn in the study by Rao and Srinivas (2006), which is that the subregions
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971 324 separated by FCXB are close to being homogeneous.

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Tab. 1. The results of discordancy and heterogeneity tests for 93 meteorological stations in SRB.

Homogeneous subregion	Containing stations Station number (D_i)	Discordancy measure $D_{critical}$	Heterogeneity Test		
			H_1	H_2	H_3
I (11 sites)	1 (0.162), 3 (0.964), 5 (0.172), 6 (0.226), 10 (2.464), 11 (1.731), 14 (0.313), 42 (0.576), 48 (2.597), 56 (0.884), 57 (0.912)	2.632	0.837	-1.863	-1.139
II (24 sites)	7 (1.444), 8 (2.467), 12 (0.270), 13 (1.091), 15 (0.704), 16 (0.292), 17 (0.046), 21 (1.098), 22 (0.796), 23 (2.692), 25 (0.214), 30 (2.582), 31 (0.079), 32 (1.511), 33 (0.270), 34 (0.918), 35 (0.842), 41 (1.092), 43 (0.428), 44 (0.520), 45 (2.702), 46 (0.687), 49 (0.816), 50 (0.440)	3	0.875	0.035	-0.585
III (14 sites)	2 (0.933), 4 (0.966), 9 (0.370), 18 (0.471), 20 (0.626), 24 (0.845), 26 (1.532), 27 (1.531), 28 (1.341), 29 (0.131), 36 (2.302), 38 (0.404), 39 (1.663), 40 (0.885)	2.971	-0.812	-0.471	-0.508
IV (17 sites)	58 (2.177), 71 (1.367), 72 (1.201), 73 (0.375), 74 (0.685), 75 (1.211), 76 (1.287), 77 (0.376), 85 (0.755), 86 (0.807), 87 (1.115), 88 (0.535), 89 (1.582), 90 (0.808), 93 (0.137), 94 (1.259), 96 (1.323)	3	-1.293	-1.213	-0.777
V (13 sites)	61 (0.811), 63 (0.568), 64 (1.725), 65 (0.437), 66 (0.425), 78 (1.198), 79 (1.086), 80 (1.120), 81 (1.563), 82 (0.275), 83 (1.935), 91 (0.477), 92 (1.380)	2.869	0.649	-0.170	-1.196
VI (14 sites)	37 (0.330), 47 (0.375), 51 (0.565), 52 (1.072), 53 (0.813), 54 (0.605), 55 (1.299), 59 (0.131), 60 (1.720), 62 (1.255), 67 (0.557), 68 (2.819), 69 (0.957), 70 (1.500)	2.971	-0.474	-0.744	-0.920

3.3 Choice of the optimal regional distribution

We first use three different goodness-of-fit measures (HWGOF, GMLM, and KPGOF) to determine the optimal regional distributions in each subregion, and their performance are then compared. Then, the CI is used to give the final decision of the choice of distribution, as it can balance the discrepancy and bias of different measures and provide a more reliable suggestion. The results of HWGOF for the four types of distributions (PE3, GEV, GNO, and GLO) are given in Tab. 2. It can be seen that GEV, PE3, and GNO can be considered as acceptable distributions for subregions I, III and VI since their $|Z^{DIST}|$ values are no more than the critical value 1.64. However, GNO, with the minimum $|Z^{DIST}|$ value, is the optimal distribution for these three subregions. Similarly, for subregions II, IV and V, GNO and GEV are both considered acceptable regional models but GEV is determined to be the best model for these subregions.

Fig. 5 presents the results of GMLM for each subregion. It indicates that GNO is the best model for subregions I, III and VI and GEV is the optimal distribution for subregion IV because their theoretical curves are the closest to the regional average L-moment ratios points compared with those of the other distributions. GNO and GEV are both considered acceptable distributions for subregions II and V since their corresponding theoretical curves are both close to the regional average L-moment ratios points, but the optimal distribution cannot be determined by GMLM.

The 95% confidence ellipses used in KPGOF for identifying the acceptable regional distributions are also shown in Fig. 5. It shows that GNO and GEV are acceptable

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1107 348 distributions for all subregions since their theoretical curves intersect the confidence
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1109 349 ellipses of all subregions. PE3 can be considered an acceptable distributions of
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1112 350 subregions I and III for the same reason. The difference between the results of HWGOF
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1115 351 and KPGOF is that PE3 is not accepted for subregion VI by KPGOF. Then, the optimal
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1117 352 regional distributions are determined from the identified candidate distributions of each
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1119 353 subregion, and the results are shown in Tab. 2. It can be found from Tab. 2 that the
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1122 354 results of KPGOF are consistent with those of HWGOF.
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Tab. 2. The results of HWGOF, KPGOF, and CI for 6 subregions in SRB
 ('NA' represents the distribution is not accepted as a candidate distribution for this region, which also means the values of these distributions are larger than the critical value of KPGOF).

Subregion	Measures	HWGOF					KPGOF					CI				
		GNO	PE3	GEV	GLO	Best model	GNO	PE3	GEV	GLO	Best model	GNO	PE3	GEV	GLO	Best model
I		0.608	-1.104	1.541	3.239	GNO	0.377	2.349	4.398	NA	GNO	0.150	0.726	0.963	1.000	GNO
II		-0.524	-2.381	0.466	3.298	GEV	0.888	NA	0.158	NA	GEV	0.503	1.000	0.106	1.000	GEV
III		0.21	-1.271	0.994	3.25	GNO	0.001	3.25	1.162	NA	GNO	0.042	0.825	0.618	1.000	GNO
IV		-0.756	-2.554	0.197	2.108	GEV	2.424	NA	0.023	NA	GEV	0.661	1.000	0.041	1.000	GEV
V		-0.413	-1.827	0.36	2.275	GEV	0.593	NA	0.127	NA	GEV	0.126	1.000	0.082	1.000	GEV
VI		-0.081	-1.583	0.686	2.767	GNO	0.14	NA	0.736	NA	GNO	0.026	0.986	0.525	1.000	GNO

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1207 359 With the results of the three measures, the final choices of the most appropriate
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1209 360 distributions for each subregion are determined by the CI. The results of CI are also
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1212 361 presented in Tab. 2, and the minimum values in the results of CI for each subregion
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1215 362 indicate that the most appropriate frequency distributions for subregions I, III and VI
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1217 363 and for subregions II, IV and V are still determined to be GNO and GEV, respectively.
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1219 364 To examine the reasonability and reliability of the results of CI, a performance
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1222 365 comparison is conducted between CI and the three other measures. Based on previous
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1225 366 studies (Hosking and Wallis, 1997; Peel et al., 2001; Vogel and Wilson, 1996) and the
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1227 367 results of three measures in this study, it can be accepted that HWGOF, KPGOF, and
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1230 368 CI are generally more reliable than GMLM, as GMLM is a subjective measure and may
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1232 369 fail to determine the optimal regional distributions in some subregions like subregions
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1235 370 II and V. The performance comparison between HWGOF, KPGOF, and CI is slightly
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1237 371 adapted from the evaluations in the studies of Hosking and Wallis (1997) and Kjeldsen
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1240 372 and Prosdocimi (2015). For each subregion, Monte Carlo simulations are used to
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1242 373 generate 500 replicas of this region according to the corresponding optimal regional
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1245 374 frequency distribution. Each replica contains the same number of stations and records
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1247 375 length as their real-world counterpart. The time series at each site in this subregion is
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1250 376 randomly generated according to the real L-moment ratios of this site and the optimal
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1252 377 regional distribution. Then, for each replica, the HWGOF, KPGOF, and CI are applied
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1255 378 to select the best distribution among GLO, GEV, GNO, and PE3. The percentages of
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1257 379 each distribution selected as the optimal one by the different measures are recorded in
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1266 380 Tab. 3. The performance comparison between HWGOF and KPGOF shows that the
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1269 381 HWGOF selects the true distributions of subregions II, IV and V more often than
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1271 382 KPGOF, while KPGOF performs better in subregions I, III and VI. In addition, it can
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1274 383 be generally accepted that both KPGOF and CI perform better than HWGOF in
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1276 384 selecting the true regional distributions, as HWGOF selects GEV more often than the
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1279 385 true distribution GNO for subregions I, III and VI, while KPGOF and CI always choose
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1281 386 the true distribution more often than the other distributions. Moreover, the performance
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1284 387 comparison between CI and KPGOF indicates that the correct regional distribution is
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1286 388 chosen more often by CI than KPGOF for all subregions except subregion I, while the
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1289 389 selected percentage difference of subregion I is not large. Furthermore, for subregions
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1291 390 II, IV and V, where HWGOF performs better than KPGOF, CI selects the true
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1294 391 distribution GEV more frequently than HWGOF. Thus, it can be concluded that CI
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1296 392 performs better than KPGOF and HWGOF in selecting the true distributions, which
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1299 393 also means that the results of CI are more reliable.

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1301 394 The advantage of CI is that it can effectively reduce the uncertainty of a single
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1304 395 measure. There exist situations in which it is hard for a single measure to identify the
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1306 396 most appropriate distribution from several alternatives with similar results (Chen et al.,
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1309 397 2014; Du et al., 2014; Hosking and Wallis, 1997). For example, in this study, it is
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1311 398 difficult to identify the optimal distributions of GNO and GEV using GMLM for
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1314 399 subregions II and V. In addition, there remains a large uncertainty in the process of
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1316 400 selecting the optimal distribution for subregion II by HWGOF, as the difference

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1325 401 between the values of GNO and GEV is quite small and may be caused by statistical
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1328 402 errors. A similar problem was found in the study by Chen et al. (2014), in which the
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1330 403 values of GNO and GEV were close when HWGOF was applied to select the optimal
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1332 404 distribution for subregion III of the Yangtze River Basin. Therefore, compared with a
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1335 405 single measure, CI can identify the differences between all candidate distributions and
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1338 406 find the most appropriate distribution accepted by the majority of robust measures,
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1340 407 which can largely reduce the uncertainties in the process of choosing the optimal
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1343 408 regional distribution. As shown in Tab. 2, GMLM or HWGOF cannot distinguish the
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1345 409 better performance of GNO and GEV in subregion II. However, CI definitely suggests
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1348 410 GEV as the best regional model since the T^{DIST} value of GEV is much smaller than
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1350 411 that of the other distributions.

1352 412 Tab. 3. The percentages of simulations where a particular selected distribution is chosen by
1353 413 HWGOF, KPGOF, and CI (the bold values represent the percentages of the true regional
1354 414 distributions selected by the three measures).

Region (best distribution)	HWGOF				KPGOF				CI			
	GLO	GEV	GNO	PE3	GLO	GEV	GNO	PE3	GLO	GEV	GNO	PE3
Subregion I (GNO)	15%	36%	30%	19%	4%	24%	44%	28%	5%	28%	40%	27%
Subregion II (GEV)	13%	66%	19%	2%	4%	62%	32%	3%	5%	67%	26%	2%
Subregion III (GNO)	9%	36%	32%	23%	1%	27%	41%	31%	2%	31%	41%	26%
Subregion IV (GEV)	30%	54%	14%	2%	13%	53%	31%	3%	12%	56%	30%	3%
Subregion V (GEV)	29%	49%	14%	8%	14%	47%	28%	11%	17%	51%	23%	10%
Subregion VI (GNO)	9%	39%	33%	19%	2%	29%	41%	28%	3%	28%	42%	27%

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1384 **415 3.4 Accuracy analysis of extreme precipitation estimations**
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1387 416 To assess the accuracy of EP estimations with different return periods in the SRB,
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1389 417 the relative RMSE (Hosking and Wallis, 1997; Yang et al., 2010a) of the estimated
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1391 418 quantiles for each station and each subregion is calculated. Tab. 4 lists the values of the
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1393 419 regional average relative RMSEs of the estimated quantiles for the six subregions. The
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1395 420 relative RMSE values of the EP estimates for the 6 subregions range from 0.054 to
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1397 421 0.160 when the return period is no more than 100 years, which indicates that these
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1399 422 quantile estimates of the EP are reliable and can be used with confidence. Similar
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1401 423 conclusions were drawn from the accuracy analysis of the EP estimations in other
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1403 424 regions of China (Chen et al., 2014; Du et al., 2014; Yang et al., 2010a). Such a
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1405 425 phenomenon implies that the estimations of the EP by RFA in most regions of China
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1407 426 can be considered accurate when the return level is less than 100 years. Meanwhile, the
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1409 427 estimated regional growth curves together with the 95% error bounds for each
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1411 428 subregion are presented in Fig. 6. Fig. 6 also shows that the quantile estimates can be
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1413 429 valid to use when the return period is less than 100 years. In addition, the estimated
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1415 430 regional growth curves of all subregions are concave, but the estimated regional growth
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1417 431 curves in most humid regions of China are convex (Chen et al., 2014; Du et al., 2014).
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1419 432 Such a result shows that the estimated EP in the SRB has a rapidly increasing tendency
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1421 433 with the increase in the return levels. In addition, the regional growth curve of subregion
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1423 434 IV is steeper than that of the other 5 regional growth curves, which indicates that the
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1425 435 EP increments in subregion IV are larger than those in the other subregions and implies
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1443 436 a high risk of EP occurrence in this subregion.
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1445 437 Tab. 4. The values of regional average RMSE of quantile estimates for 6 subregions in SRB.

Return period \ RMSE	Sub-region I	Sub-region II	Sub-region III	Sub-region IV	Sub-region V	Sub-region VI
1 year	0.097	0.104	0.076	0.102	0.100	0.085
2 years	0.061	0.056	0.054	0.063	0.056	0.056
10 years	0.093	0.086	0.079	0.093	0.087	0.083
50 years	0.155	0.147	0.130	0.160	0.152	0.135
100 years	0.187	0.182	0.156	0.209	0.185	0.165

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1457 439 3.5 Return period analysis

1460 440 The spatial patterns of the EP under different return periods, which can serve as an
1461 441 important indicator for the risk analysis, are investigated with the estimated EP of each
1462 442 station and the spatial interpolation method. In this study, the Inverse Distance
1463 443 Weighting method is adopted to obtain spatial maps of the EP in the SRB under
1464 444 different return periods (T=1, 5, 10, 50 and 100 years), and these spatial maps are
1465 445 presented in Fig. 7. It can be found that the estimated precipitation extremes of the
1466 446 different return periods in the SRB present similar spatial variabilities. The values of
1467 447 the estimated EP decrease from the southern SRB to northern SRB, which means that
1468 448 the values of the estimated EP in subregions IV and V are larger than those in the other
1469 449 subregions. Moreover, the maximum values of the EP can be found in the south of
1470 450 subregions IV and V near the China Yellow Sea and China Bohai Sea, while the
1471 451 minimum extreme values are usually located in the north of subregion I and the
1472 452 northeast of subregion III.

1482 453 Therefore, the spatial patterns reveal that the estimated EP in the southern subregions
1483 454 (subregions IV and V) of the SRB is much larger than that in the other subregions under

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1502 455 the same return period, which means that the risk of high-intensity floods is higher in
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1504 456 the southern SRB. The main reasons behind the high values of the EP in the southern
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1507 457 SRB can be illustrated from two aspects. First, the increase in precipitation in the
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1510 458 southern SRB is related to the influence of the strong variations of the East Asian
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1512 459 monsoon, while the impact of the monsoon is not obvious in the northern SRB. In
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1514 460 addition, the water vapor pressure is higher in the southern SRB in the summer because
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1517 461 most of the water vapor in the SRB comes from the south or, more specifically, from
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1520 462 the Bay of Bengal and the western equatorial Pacific Ocean (Wu et al., 2017).

1521 463 **4 Conclusions**

1523 464 In this study, a modified L-moments method is used for a regional extreme
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1526 465 precipitation frequency analysis for the Songliao River Basin (SRB). The uncertainties
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1528 466 in the identification of homogeneous subregions and in the selection of optimal regional
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1531 467 frequency distributions can largely influence the results of the RFA and should be
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1533 468 carefully addressed. Based on the original regional L-moments method, the fuzzy c-
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1536 469 means method with the extended Xie-Benn index (FCXB) is applied to help determine
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1538 470 the optimum number of subregions in the process of identifying homogeneous
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1541 471 subregions. Moreover, we develop a new comprehensive index (CI), which gives an
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1543 472 integrated consideration to three different goodness-of-fit measures, to reduce the
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1546 473 uncertainties in regional frequency distribution. Moreover, the accuracy of the
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1548 474 estimated quantiles and the spatial distributions of the estimated precipitation extremes
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1551 475 in the SRB are also calculated and analyzed. The main conclusions of this study can be
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1553 476 given as follows:

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1561 477 1) No significant change trends can be detected in the AMP series at any stations in
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1563 478 the study area. The FCXB suggests that the whole SRB can be divided into six
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1566 479 homogenous subregions, and this division is more reliable compared with the
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1569 480 results of other cluster methods.
- 1571 481 2) The results of CI suggest that GNO is the optimal distribution for subregions I, III
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1573 482 and VI and GEV is the best distribution for subregions II, IV and V. The
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1576 483 performance comparisons between HWGOF, GMLM, KPGOF, and CI showed that
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1578 484 the CI is the most reliable measure of all, as the objective measure CI can select the
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1581 485 true distribution more often than the other measures. The results also show that
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1584 486 KPGOF performs better than HWGOF since HWGOF selects GEV more often than
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1586 487 the true distribution GNO for subregions I, III and VI. In addition, the CI can
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1589 488 effectively reduce the uncertainty in the selection of optimal distributions when the
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1591 489 distributions suggested by different single measures show differences.
- 1593 490 3) The values of the relative RMSE of the estimated precipitation extremes for the 6
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1596 491 subregions range from 0.054 to 0.160 when the return period is no more than 100
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1599 492 years, which indicates a high confidence for the quantile estimates of extreme
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1601 493 precipitation.
- 1603 494 4) The spatial distributions of the precipitation extremes in the SRB with different
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1606 495 return periods (T=1, 5, 10, 50 and 100 years) all show similar decreasing trends
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1609 496 from the southern SRB to the northern SRB. Thus, the southern subregions in the
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1611 497 SRB (subregions IV and V) have a higher risk of high-intensity floods than the

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1620 498 northern subregions.
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1623 499 The results of this study prove that FCXB and CI are two reliable and effective
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1625 500 methods that can help obtain a more robust and reliable result of RFA. This study can
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1628 501 also be beneficial for finding the regions in the SRB prone to suffering from EP events
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1630 502 and can provide scientific support for local policymakers to determine corresponding
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1633 503 measures to reduce losses to the minimum level.

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1651 511 **References**

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631 **List of Fig. Captions**

632

633 Fig. 1. The location of the Songliao River Basin (SRB) in the northeastern China. The
634 meteorological stations are represented by the red triangle points. The underlined words in
635 black color represent the names of provinces, and IN, LN, JL, and HLJ represent Inner
636 Mongolia province, Liaoning province, Jilin province, and Heilongjiang province, respectively.
637 The gray italic words are the abbreviated names of main rivers. From the top to the bottom of
638 this Fig., EGR, AR, NR, SHR, SST, LR, SFR, DLR, TMR, YLR represent Ergun River, Amur
639 River, Nenjiang River, Songhua River, Second Songhua Tributary, Liao River, Suifen River,
640 Daling River, Tumen River, Yalu River, respectively.

641 Fig. 2. The boxplot of the Mann Kendall test results of 93 stations (a). The red horizontal dash lines
642 represent the critical value (± 1.96) for the MK test at 5% significance level. The spatial pattern
643 of the Mann-Kendall test result for the SRB over the period 1960–2016 (b). The red triangle

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644 points and blue circle points indicate the stations with increasing and decreasing trends,
645 respectively.

646 Fig. 3. The values of the extended Xie-Benn index with different numbers of subregions.

647 Fig. 4. The division of 6 homogeneous subregions in SRB (a) and the long-term annual mean
648 precipitation of each subregion (b).

649 Fig. 5. The L-diagrams for AMP at 6 subregions. The black circle points represent L-skewness and
650 L-kurtosis of each station, the plus signal points represent the regional average L-skewness and
651 L-kurtosis. The black ellipses represent the confidence regions with the 5% significance level.

652 Fig. 6. The estimated regional growth curves of AMP with 95% error bounds for six subregions.
653 The red lines represent the regional growth curves and the black lines represent the 95% error
654 bounds, and the grey shadow regions denote the confidence intervals.

655 Fig. 7. The spatial distributions of estimated precipitation extremes in SRB when the return period
656 equals to 1, 5, 10, 50 and 100 years.

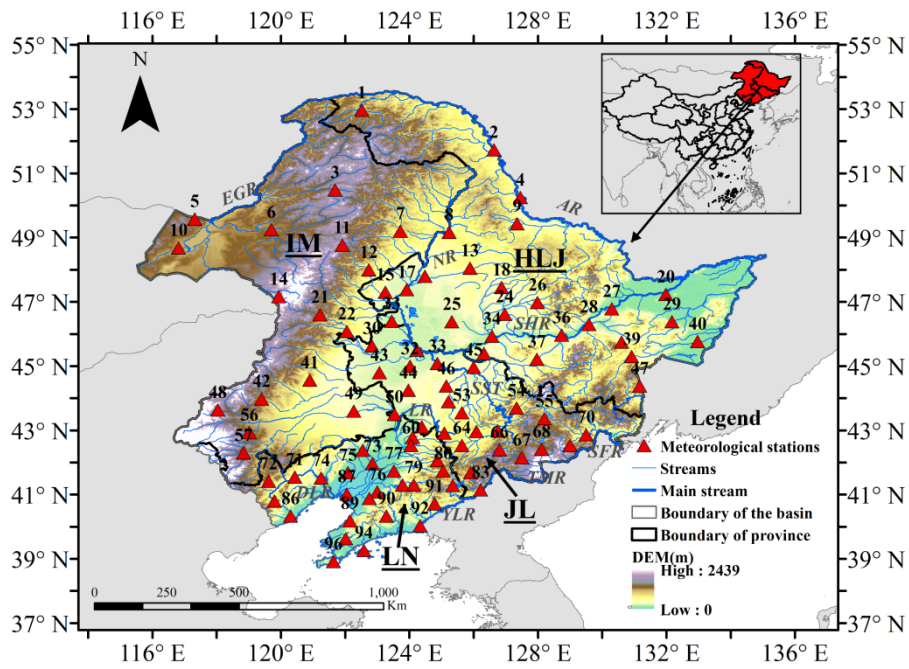


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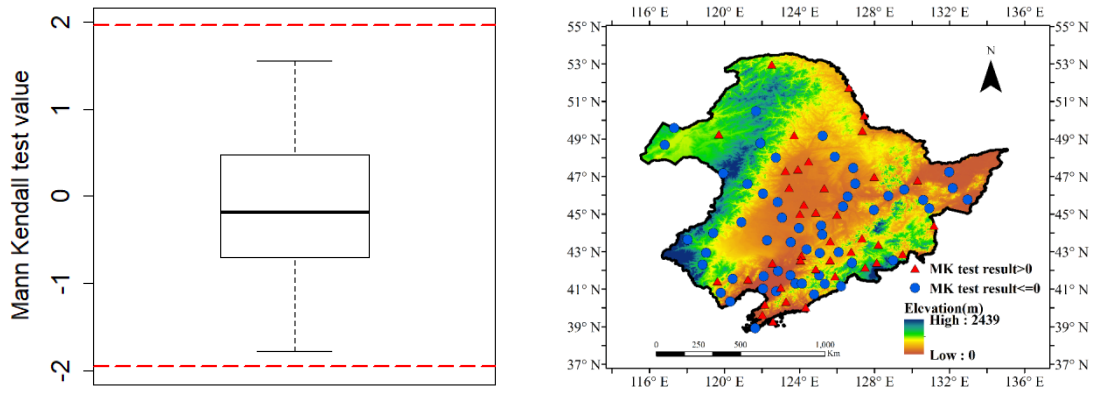


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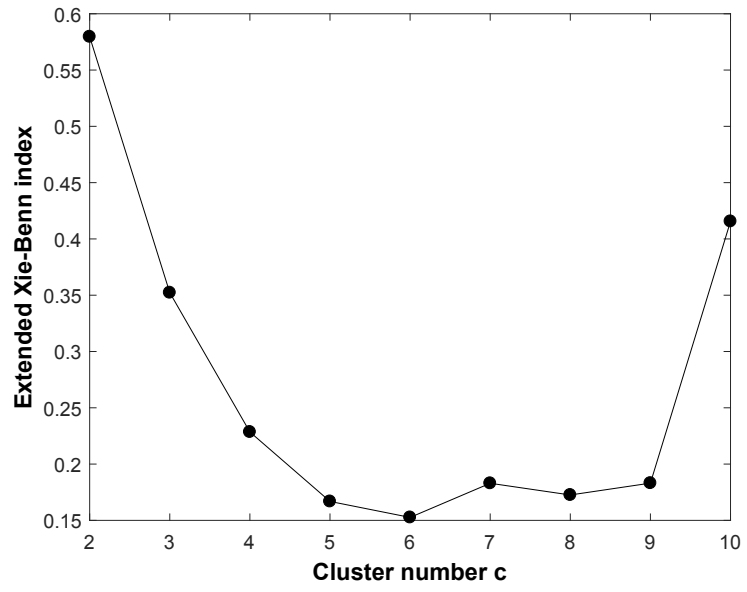
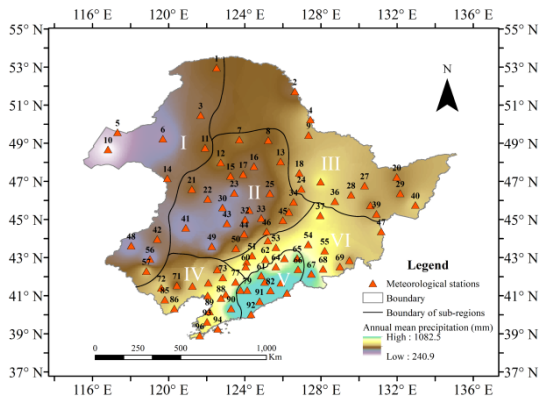
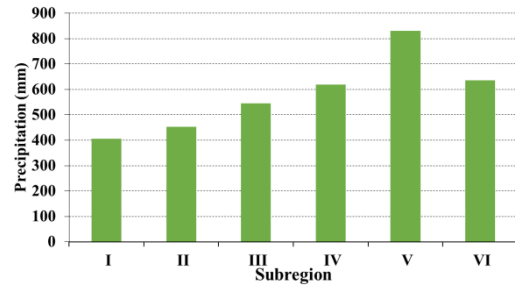


Fig.3. The values of the extended Xie-Benn index with different numbers of subregions.



(a)



(b)

Fig.4. The division of 6 homogeneous subregions in SRB (a) and the long-term annual mean precipitation of each subregion (b).

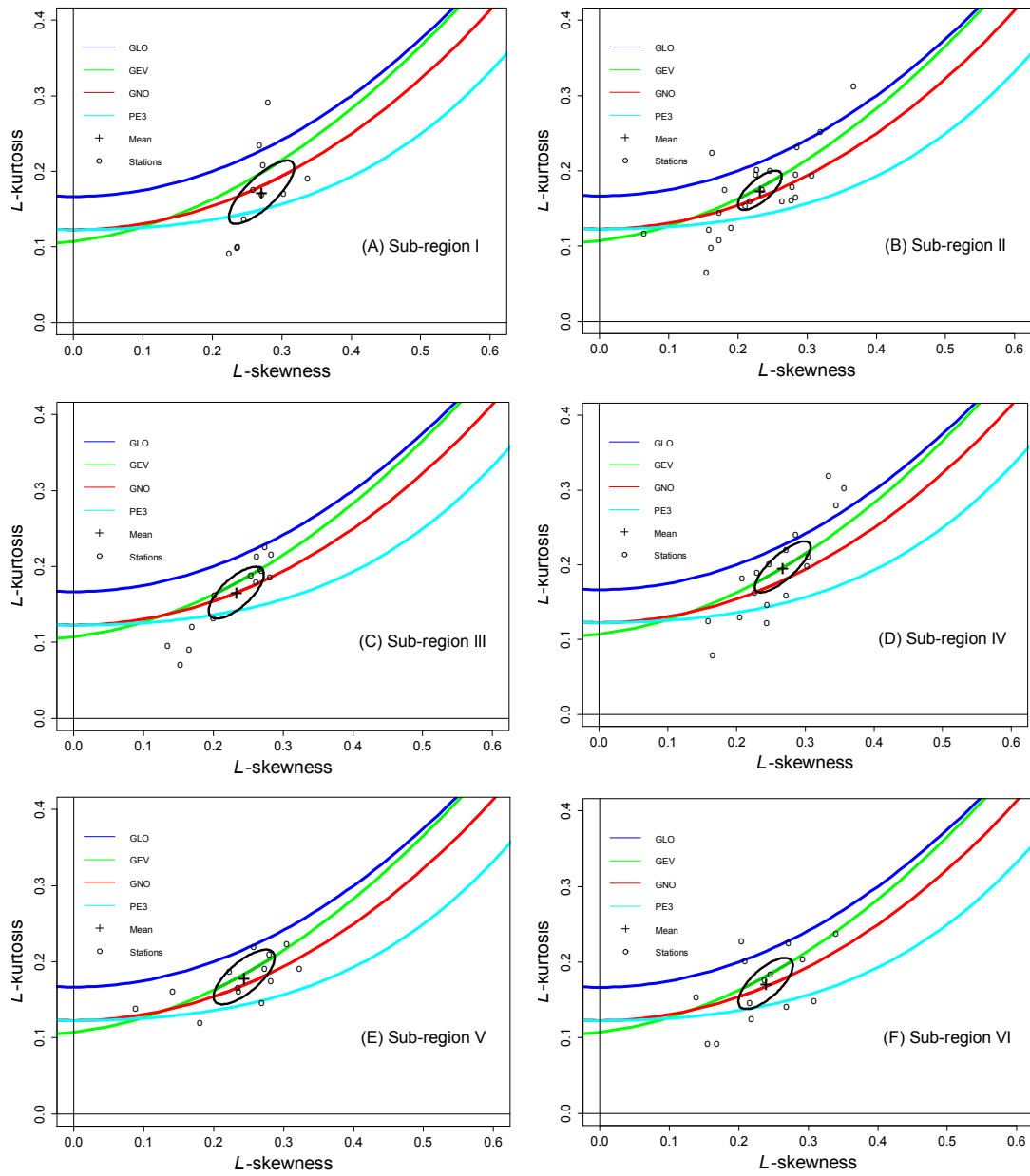


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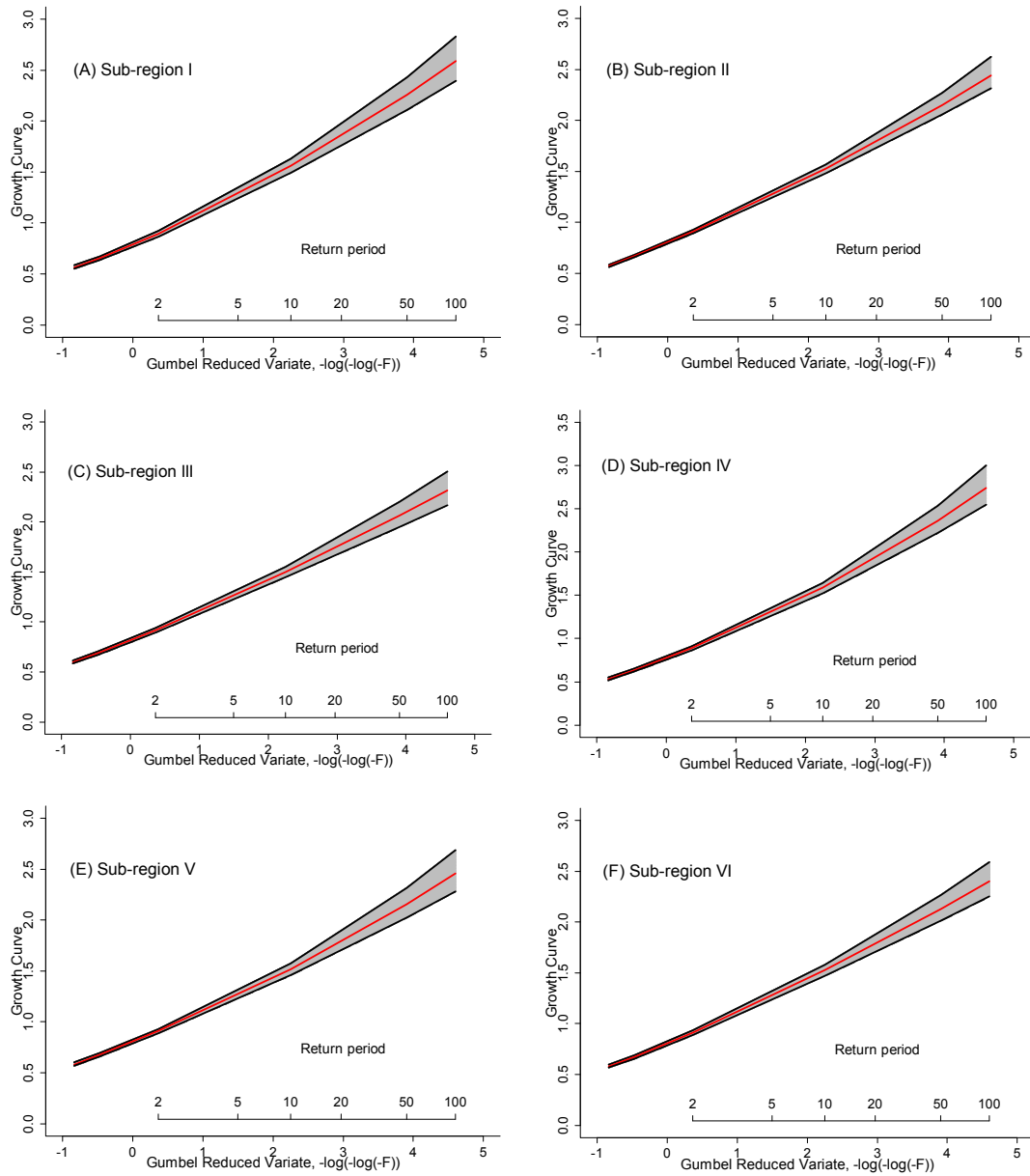


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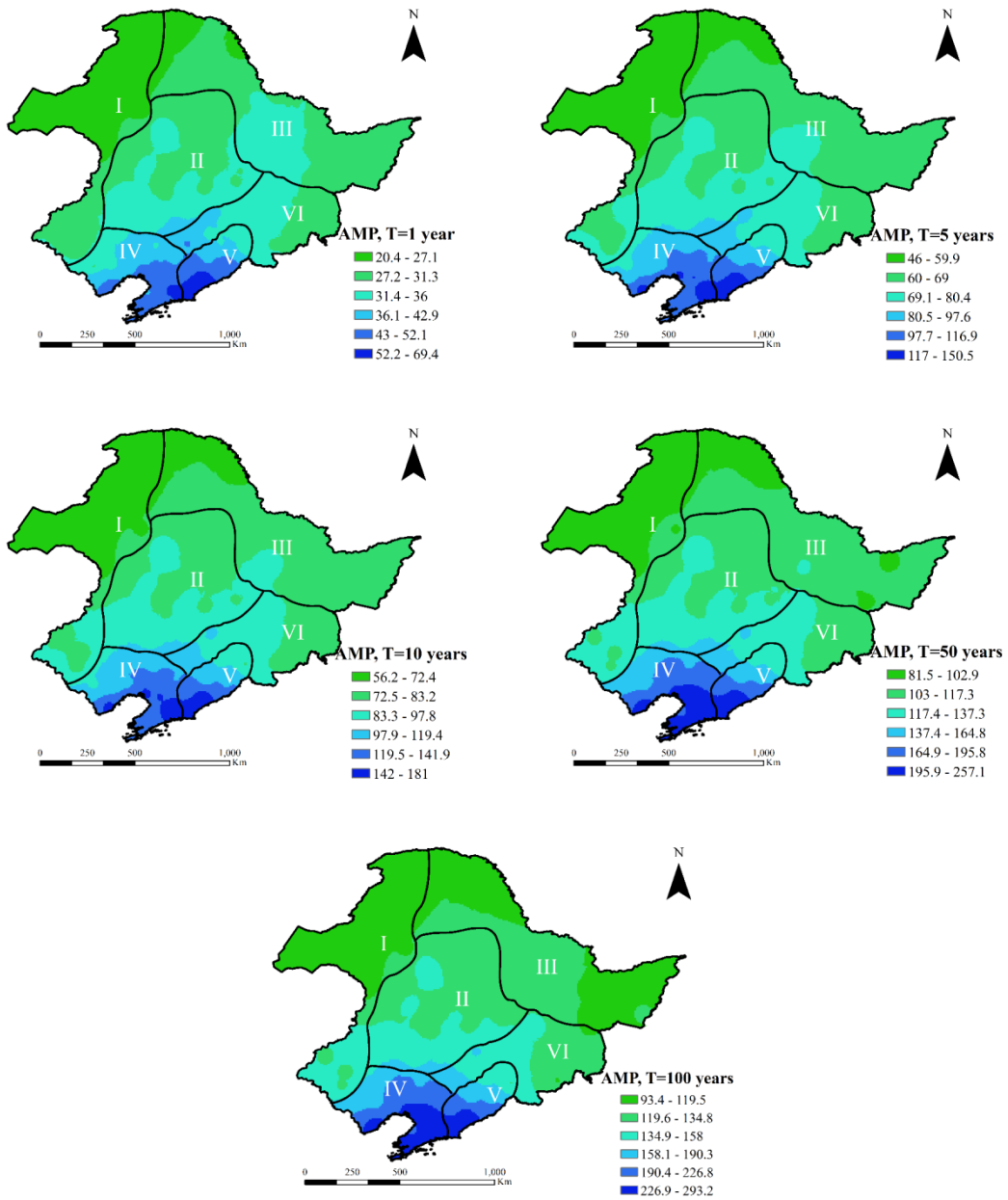


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