



23 period in different periods and to analyze the characteristics of heavy precipitation
24 causing disasters in Shandong Province on this basis. Compared with the disaster
25 return period calculated by relying on univariate variables, the Copula function can
26 more reasonably simulate the natural occurrence of the degree of disaster. The joint
27 return period (JRP) estimated by the Copula function shows that the JPR of heavy
28 rainfall with a duration of 1 hour is 89% higher than that of 6 hours, indicating a
29 significant increase in the risk of disasters caused by short-term heavy rainfall in
30 Shandong region. This method can more scientifically describe the risk of disasters
31 caused by heavy precipitation in different scenarios, especially the characteristics of
32 disasters caused by short-term heavy precipitation, which can provide an adequate
33 scientific basis for disaster prevention and mitigation planning and disaster risk
34 management.

35

36

KEYWORDS

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Copula joint distribution; heavy rainfall; recurrence period

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40

1. INTRODUCTION

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44

In its 6th Assessment Report on Climate Change, the IPCC states that, as a result
of global warming, the frequency and intensity of heavy precipitation events may
increase in the 21st century as a result of human activities and changes in natural



45 systems if future warming is not limited to 1.5 degrees Celsius, and that there is a
46 consensus in the IPCC that the frequency and intensity of heavy precipitation events
47 may increase in the 21st century as a result of human activities and changes in natural
48 systems (Zhou et al., 2024).

49 Heavy precipitation, as an essential form of extreme weather and climate events,
50 is a natural phenomenon that frequently occurs in different regions of the globe and is
51 prone to induce derivative hazards, such as flash floods, geological hazards, and urban
52 waterlogging, with far-reaching impacts on food security, economic activities, and
53 water resources. For example, the flooding caused by heavy precipitation in Shandong
54 on 9 August 2010 resulted in 1,243,700 people being affected, with crops affecting an
55 area of 159.1,000 hectares, including 16.6,000 hectares of crops that were out of
56 harvest, nearly 3,000 houses collapsed, nearly 2,300 houses damaged, and a direct
57 economic loss of 520 million yuan. It is, therefore, essential for disaster prevention
58 and mitigation to quickly assess the return period of extreme precipitation disasters
59 and to increase monitoring and forecasting efforts.

60 The return period, which measures how often the hazard from heavy
61 precipitation exceeds a certain threshold, is significant for understanding regional
62 risks due to heavy precipitation and addressing possible future climate challenges.
63 While previous studies have recognized the importance of return period indicators as
64 a means of quantifying the risk of disasters such as heavy precipitation and droughts,
65 the essence of the evaluation methodology is to reduce multi-influence factors to
66 univariate ones, resulting in the loss of correlation information on the vital



67 disaster-causing factors in the reliance on a univariate approach to portraying the
68 return period (Cheng et al., 2022; Tan et al., 2023). In order to avoid the problem of
69 overestimation or underestimation of the return period caused by relying on univariate
70 calculations, some scholars have attempted to establish a multivariate model for
71 portraying the risk of disaster-causing events (Vergni et al., 2015; Wang et al., 2023).
72 However, traditional multivariate models need to ensure that the variables are
73 independent of each other and, at the same time, obey a specific type of marginal
74 distribution (Zhang et al., 2007). Independence between variables is difficult to satisfy
75 in real disaster-causing scenarios, and it is difficult to satisfy the prerequisite of
76 obeying a specific marginal distribution simultaneously. Therefore, the approach of
77 premising multivariate models on extreme assumptions only applies to some
78 disaster-causing scenarios. In this paper, we consider multivariate models premised on
79 relatively flexible assumptions to analyze the probability of heavy precipitation.

80 In recent years, some scholars have proposed using the Copula function to
81 portray multivariate dependencies more flexibly in various disaster-causing scenarios
82 and to overcome the constraints of the assumptions that satisfy both the independence
83 and the marginal distribution types (Sklar, 1959). Copula functions have been widely
84 used in drought event risk identification. Li et al. (2015) studied the joint return period
85 of drought events in Beijing and assessed the impact of drought risk on winter wheat
86 growth. Zhang et al. (2022) used a multivariate risk assessment method based on
87 Copula functions to analyze the return period of high-temperature compound drought
88 events in the Yangtze River Basin. Wen et al. (2023) established a drought risk model



89 through copula functions to reveal the response relationships among drought variables
90 in Henan Province.

91 Meanwhile, the Copula function has also been applied in disaster risk analysis of
92 flooding events; De Michele et al. (2023) first proposed the use of the Copula
93 function to portray the frequency of heavy precipitation and fitted the relationship
94 between the duration of natural precipitation and the intensity of precipitation through
95 the generalized Pareto distribution. X Tong et al. (2015) analyzed the variation of
96 flood data over time using selected Copula models. Haile M M et al. (2023)
97 demonstrated the effectiveness of Copula in flood management through binary
98 modeling of flood peak and flood volume characteristics. The above studies have
99 shown that the Copula function is an effective tool for analyzing extreme events such
100 as droughts or floods. However, the studies on the disaster risk of heavy precipitation
101 events have mainly focused on analyzing the frequency characteristics of heavy
102 precipitation through the daily precipitation amount and the number of days of
103 precipitation. It is difficult to highlight the disaster-causing hazards associated with
104 short-calendar duration heavy precipitation events (Utsumi N et al., 2022).

105 In order to solve these problems, this study establishes a joint probability density
106 distribution model of precipitation time and precipitation amount based on
107 hourly-scale precipitation data. It analyses the long-term change characteristics of
108 heavy precipitation, based on which we analyze the disaster-causing risk of
109 short-calendar-time heavy precipitation in Shandong, which can assess the impacts of
110 short-term heavy precipitation more accurately, quantitatively, and scientifically. The



111 purpose of the study is to construct the joint probability density distribution of
112 precipitation duration and precipitation amount through the Copula function and to
113 use this function to calculate the return period, based on which to carry out the
114 research related to the frequency of heavy precipitation and the spatial distribution
115 characteristics of the coupling of heavy precipitation duration and precipitation
116 amount in Shandong, and to analyze the changes and connections of the
117 multi-scenarios of heavy precipitation in the Shandong region from the viewpoint of
118 the return period, and to obtain the frequency of heavy precipitation and the spatial
119 and temporal distribution characteristics and the disaster risk of the heavy
120 precipitation in Shandong. The spatial and temporal distribution characteristics of
121 heavy precipitation frequency in Shandong and the disaster risk can be based on the
122 above results to derive the countermeasures of heavy precipitation in different
123 recurrence periods. The study has a positive effect on improving disaster prevention
124 and mitigation during flood seasons and the ability to make scientific decisions,
125 especially in the Asian region, where population densities are in the billions, to
126 effectively monitor and predict the level of hazards posed by heavy precipitation. The
127 study has a positive effect on improving disaster prevention and mitigation during
128 flood seasons and the ability to make scientific decisions, especially in the Asian
129 region, where population densities are in the billions, to effectively monitor and
130 predict the level of hazards posed by heavy precipitation.

131 The structure of this article is as follows. Section 2 introduces a dataset used to
132 simulate the recurrence period of heavy precipitation and various disaster scenarios



133 caused by heavy precipitation. Section 3 introduces the definition of the edge
134 distribution function used in the Copula model, explains how to use appropriate
135 testing methods to select the optimal type of edge distribution function, and explains
136 how to calculate the return period of joint precipitation duration and precipitation.
137 Section 4 statistically analyzed the marginal probability distribution of various
138 disaster causing factors in heavy precipitation events and the joint distribution
139 characteristics of the binary Copula model, and evaluated the improvement results of
140 the joint recurrence period compared to the univariate recurrence period. It simulated
141 the spatial distribution changes of multiple scenario heavy precipitation recurrence
142 periods and analyzed the frequent occurrence scenarios and key determining factors
143 of heavy precipitation disasters. For example, we found that the recurrence interval of
144 a scenario with a duration of 1 hour of heavy precipitation was much higher than the
145 threshold of 6 hours for heavy precipitation duration. Compared with the average
146 frequency of occurrence of heavy precipitation events within 1 hour, the frequency
147 increased by 89%, resulting in an increased risk of disaster. Section 5 summarizes the
148 research results and provides a more in-depth discussion on potential applications.

149

150 **2. MATERIALS**

151

152 **2.1. The Definition of a severe heavy rainfall**

153

154 Extreme precipitation is a measure of rainfall that generally refers to highly



155 intense and destructive rainfall. Extreme precipitation events, as one of the
156 manifestations of extreme weather events, are highly susceptible to secondary
157 disasters, such as flash floods and mudslides in small watersheds, and have caused
158 enormous losses in many countries and regions of the world. According to the
159 definition of extreme weather indicators recommended by WMO, rainfall events with
160 daily rainfall exceeding 95% and 99% quartiles are defined as heavy and extremely
161 heavy rainfall events, respectively. Internationally, indicators such as annual extreme
162 precipitation, frequency of occurrence, extreme precipitation intensity, and annual
163 maximum daily precipitation are usually chosen to study the characteristic patterns of
164 extreme precipitation events.

165 According to the China Meteorological Administration (CMA), heavy
166 precipitation events are defined as rainfall of 16 mm or more in one hour or 50 mm or
167 more in 24 hours, and heavy rainfall is further classified into general rainstorms,
168 heavy rainstorms, and hefty rainstorms according to the intensity of the precipitation.
169 An average rainstorm is defined as less than 70 millimeters in 12 hours or less than
170 100 millimeters in 24 hours, while a heavy rainstorm is defined as more than 70
171 millimeters but less than 140 millimeters in 12 hours, and a hefty rainstorm is defined
172 as more than 140 millimeters in 12 hours or more than 200 millimeters in 24 hours.
173 Therefore, the case studies of rainfall events in this paper include heavy rainfall and
174 weighty rainfall events to analyze the characteristics of changes in disaster-causing
175 factors in different scenarios from the perspective of heavy precipitation disaster
176 prevention and mitigation.



177

178 **2.2. Data Used**

179

180 The data used in this paper are hourly precipitation data from 122 national
181 stations in Shandong (Fig. 1) for May-September 1990-2023, with the original data
182 coming from the consolidated data of the Meteorological Data Centre of Shandong
183 Province after removing dubious and erroneous data through quality control. For
184 hourly precipitation compilation data with more than 30 years of observation (the
185 reference year for climate averages), precipitation processes with 1-hour intervals are
186 combined into a single precipitation event. The cumulative precipitation of the event
187 is screened to see if the cumulative precipitation of the event is greater than or equal
188 to 15 mm. The precipitation intensity is greater than $5 \text{ mm} \cdot \text{h}^{-1}$ to obtain a heavy
189 precipitation event (She et al., 2011; Wang et al., 2023). This paper calculates the
190 return period based on a sample of heavy precipitation events.

191 From the records of the Shandong Meteorological Bureau of extreme
192 precipitation events from 1990 to 2023, it can be seen that 122 stations in Shandong
193 have experienced heavy precipitation within 1 hour, with an average of about 157
194 occurrences, the longest average duration of 7 h, and the shortest average duration of
195 4 h. The average precipitation of the heavy precipitation process at each station is 47
196 mm. The maximum average precipitation occurs at 59 mm, the most extended
197 duration of the most precipitation process is 79 h, and the maximum precipitation is
198 595 mm. The average precipitation amount of the heavy precipitation process at each



199 station is 47 mm, the maximum average precipitation amount is 59 mm, the most
200 extended duration of the most precipitation process is 79 h, and the maximum
201 precipitation amount is 595 mm. The Kendall rank correlation coefficients of
202 precipitation amount and precipitation duration are between 0.4 and 0.8, and there is a
203 significant correlation between heavy precipitation duration and precipitation amount,
204 which is suitable for establishing the joint probability density distribution.

205

206 **3.COPULA-BASED RETURN PERIOD**

207

208 **3.1. Copula's theoretical foundations**

209

210 The Copula function originates from Sklar's theorem in 1959 ⁽⁷⁾, also known as the
211 "connection" function, i.e., if there are two random variables that have their own fitted
212 marginal distribution function, then you can find a unique joint distribution function
213 to "connect" the marginal distributions of the two variables, making the Copula
214 function "connect" the marginal distributions of the two variables. Copula function
215 that "connects" the marginal distributions of the two variables such that

$$216 \quad J(x,y) = C(u(x),v(y))J(x,y) = C(u(x),v(y)) \quad (1)$$

217 Equation (1) is a binary joint distribution function containing continuous marginal
218 distributions and features. From the above equation, the structure of the Copula
219 function can be independent of a particular marginal distribution function and,
220 therefore, can better characterize the dependent structure of two random variables.



221 This paper selects Gumbel, Frank, and Clayton, who are in the Copula function
222 cluster, as candidates. The above three Copula distribution functions and their
223 parameter value ranges are given in Table 1. The maximum likelihood estimation
224 method is used to obtain the parameters of the Copula marginal distribution function.
225 The fit of the candidate Copula function was tested according to the AIC (Akaike
226 information criterion) method, and the smaller the test value, the better the fit of the
227 function (Jiang et al., 2008; Song et al., 2023).

228

229 **3.2. Identification of the Appropriate Marginal distribution function**

230

231 The selection of an appropriate marginal distribution function is a prerequisite
232 for constructing a Copula joint distribution model for heavy precipitation events, and
233 a specific marginal distribution function is often chosen in previous characterization
234 studies of heavy precipitation (Wang et al., 2006; Ummul et al., 2014; Salvadori et al.,
235 2015). Considering the variability of the probability distribution of heavy
236 precipitation events in different regions and the reliability of the model estimation
237 results, six candidate marginal distribution functions (Table 2), which are the most
238 widely used in natural sciences and engineering, are selected the candidate marginal
239 distribution functions are Gamma (Gam), Weibull (Wbl), Exponential (Exp),
240 Lognormal (Ln), Generalised Extreme Value (Gev), Generalised Pareto (Gp), and the
241 parameters of the marginal distribution were estimated using maximum likelihood
242 estimation. Comparison of the goodness of fit of candidate marginal distribution



243 functions using the K-S (Kolmogorov-Smirnov) test (Frank et al., 1951; Li et al.,
244 2024). The optimal marginal distribution fitting functions for the duration of heavy
245 precipitation and the amount of precipitation at each station in each region of
246 Shandong are determined sequentially.

247

248 **3.3. Calculation of the Return Period**

249

250 When a single variable is critical to the assessment of the risk of heavy
251 precipitation, it is reasonable to assess the level of hazard based on the return period
252 estimated by a single variable, and when a single variable is deterministic or the
253 correlation is weak between two variables, a return period that relies on the
254 cumulative amount of precipitation from a single precipitation process being greater
255 than or equal to a certain threshold is defined as univariate return period. Assume that
256 the marginal distribution function of heavy precipitation is $u(x)$; the univariate return
257 period is calculated as:

$$258 \quad T_w = \frac{T}{N(1-u(x))} T_w = \frac{T}{N(1-u(x))} \quad (2)$$

259 Where T is the number of years in the time series at the study site, and N is the
260 number of heavy precipitation events that occurred.

261 When the risk of heavy precipitation is influenced by the combination of two
262 variables, for example, the degree of damage caused by heavy precipitation is closely
263 related to the duration and amount of precipitation, usually the shorter the duration of
264 heavy precipitation and the more precipitation, the greater the degree of risk of



265 damage. The joint return period algorithm constructed using the Copula function can
266 calculate the frequency characteristics of heavy precipitation under the joint influence
267 of two variables. In the case of heavy precipitation events, the joint return period can
268 be used to characterize the situation where heavy precipitation events are more
269 catastrophic in a short period; considering that there is more heavy precipitation
270 during the flood season in Shandong, the joint return period is defined:

$$271 \quad T_C = \frac{T}{N \cdot P(X \geq x | Y \leq y)} = \frac{T}{N \cdot (1 - C(u(x), v(y)) / v(y))} \quad (3)$$

272 where $P(X \geq x | Y \leq y)$ is the conditional probability of an intense precipitation event
273 with process precipitation greater than x and precipitation duration less than y (Shen
274 et al., 2013).

275

276

4. RESULTS

277

278 **4.1. Characteristics of the marginal probability distribution of heavy** 279 **precipitation events**

280

281 In order to select appropriate types of fitted marginal probability distributions for
282 precipitation duration and precipitation amount, the six candidate marginal probability
283 distributions were tested for goodness-of-fit by the K-S test, and the marginal
284 distribution function with the most miniature K-S test statistic and a p-value greater
285 than 0.05 was selected as the optimal type of fitting function. In the case of heavy
286 precipitation of more than 50 mm with a duration of less than six h at Laoshan Station



287 in Qingdao City, Shandong Province, for example, based on the above test method,
288 the optimal fitting function type of the marginal probability density function of the
289 precipitation duration is the generalized extreme value distribution (Gev). The optimal
290 fitting function type of the precipitation amount is also the generalized extreme value
291 distribution (Gev). The suitability of the above two marginal distributions is verified
292 by comparing the six candidate marginal distributions of the precipitation duration
293 and precipitation amount at Laoshan Station. The fit degree of the above two marginal
294 distributions is verified by comparing the matching degree of the six candidate
295 marginal distributions of precipitation duration and precipitation amount (Fig.2).
296 Therefore, the optimal function type for the matching of precipitation duration and
297 precipitation amount at Laoshan Station is selected as the generalized extreme value
298 distribution. By counting the optimal fitting function types for 122 stations in
299 Shandong (Fig.3), it can be seen that the optimal fitting function types for
300 precipitation duration and precipitation amount are dominated by the generalized
301 extreme value (Gev) and lognormal (Ln) distributions and the optimal function type
302 for 1% of the precipitation with precipitation duration as an indicator is the Weber
303 distribution (Wbl). Overall, the duration of heavy precipitation events and the
304 marginal distribution of precipitation are suitable for selecting the generalized
305 extreme value (Gev) and lognormal (Ln) distribution types.

306
307

308 **4.2. Characterisation of the joint binary Copula distribution**

309



310 In order to select the optimal binary Copula joint distribution type for heavy
311 precipitation events, this paper adopts the AIC method to test the fit matching degree
312 of the three candidate Copula functions; the smaller the AIC value indicates that the
313 selected family of functions has a higher degree of matching for the site where the fit
314 is located, and accordingly selects the optimal matching type of the Copula function
315 for heavy precipitation events. The percentage of the optimal joint distribution
316 function types for the scenarios with different lengths of heavy precipitation and
317 precipitation amounts of 50 mm or more is statistically derived (Fig. 4). It can be seen
318 that the scenarios with precipitation durations of more than 10 h are suitable for the
319 Clayton Copula joint distribution function type. In contrast, the scenarios with
320 precipitation durations of less than 10 h have the applicable joint distribution function
321 types dominated by the Gumbel Copula and the Clayton Copula. Gumbel Copula and
322 Clayton Copula are the main types of joint distribution functions, and the above two
323 types of joint distribution functions fit well for most stations in Shandong. In addition,
324 it can be seen from Fig. 5 that the optimal fitting function type is Frank Copula for the
325 scenario of precipitation duration of 9 h with precipitation more significant than 50
326 mm, which indicates that the distribution type of heavy precipitation in the above
327 areas has some unique characteristics compared with the areas where the Gumbel
328 Copula joint distribution function was applied before, and the characteristics of the
329 heavy precipitation need to be further investigated. Thus, the Copula joint distribution
330 of heavy precipitation is constructed and completed, laying the foundation for
331 analyzing the region's heavy precipitation recurrence period and catastrophicity.



332

333 **4.3 Analysis of the results of the reproduction period improvement**

334

335 In order to analyze the trend between the precipitation duration and the estimated
336 joint return period for scenarios with cumulative precipitation more significant than
337 50 mm in Shandong, it is evident from the plot of the duration of heavy precipitation
338 with the joint return period in Shandong (Fig.5) that the joint return period gradually
339 decreases with the prolongation of the duration of heavy precipitation. When the
340 duration of heavy precipitation is less than 8 h, the joint return period decreases more
341 obviously. When the duration is more significant than 8 h, the joint return period
342 gradually approaches 0 and stabilizes. The trend of the variation of the difference rate
343 between the joint and univariate return periods of heavy precipitation (Fig.5) shows
344 similar characteristics, with the difference rate being more apparent when the duration
345 is less than 8 h and decreasing rapidly when the duration is more significant than 8 h.
346 The results show that the frequency of heavy precipitation can be calculated by
347 combining the duration and precipitation amount in a short-calendar-time scenario,
348 which is essential for the scientific analysis of the hazardous risk. The above results
349 show that in the short-calendar-time heavy precipitation scenario with a duration of
350 less than 8 h, it is essential to calculate the frequency of heavy precipitation by
351 combining the duration and precipitation amount to scientifically analyze the disaster
352 risk of heavy precipitation.

353 By analyzing the relationship between the joint and univariate reproduction



354 periods of different precipitation durations at Laoshan Station (Fig. 6), it can be found
355 that under the scenarios of 12 h and 6 h, when the duration of heavy precipitation is
356 the same, the joint reproduction period is prolonged accordingly along with the
357 increase of precipitation. When the precipitation is the same, the joint reproduction
358 period is prolonged accordingly, along with a decrease in the duration of heavy
359 precipitation. The joint reproduction period is also lengthened when the duration of
360 heavy precipitation decreases with the same precipitation amount. The Copula
361 function for estimating the joint return period takes into account both the duration of
362 heavy precipitation and the amount of precipitation, i.e., the average precipitation
363 intensity of heavy precipitation, which implies that for the same amount of
364 precipitation, the shorter the duration of heavy precipitation, the higher the average
365 precipitation intensity, the lower the probability of occurrence, and the longer the joint
366 return period, which means that under the same conditions of disaster, the hazard level
367 of this type of heavy precipitation event will also increase. This indicates that the risk
368 of such heavy precipitation events will increase under the same host conditions.
369 Therefore, estimating the joint return period using the Copula function can distinguish
370 the degree of disaster-causing hazard in different heavy precipitation scenarios.

371 From the results of the joint reproduction period for the 24-hour duration of
372 heavy precipitation in Fig.6, it is evident that it is almost the same as the results of the
373 univariate reproduction period. Compared with the estimation method of the
374 univariate return period, the joint return period is the frequency of occurrence of a
375 specific type of heavy precipitation scenario estimated under the condition that the



376 duration of heavy precipitation is less than a certain threshold. The univariate return
377 period is the frequency of occurrence of heavy precipitation events estimated based on
378 the amount of precipitation, so the difference between the two estimation methods is
379 more minor when the duration of the heavy precipitation is longer. The difference
380 between the two estimation methods is close to 0 when the threshold value of the
381 duration of the heavy precipitation is large enough. Values of the reproduction period
382 estimates have a difference close to zero. The most extended precipitation duration of
383 the heavy precipitation events in the last three decades at Laoshan station is only 21 h,
384 which is smaller than the heavy precipitation duration of 24 h estimated by the joint
385 recurrence period; therefore, when the threshold value of the duration of heavy
386 precipitation at Laoshan station is the scenario with 24 h, the results of its univariate
387 recurrence period and the joint recurrence period are almost the same.

388 It is noteworthy that, in the disaster risk assessment of heavy precipitation
389 processes, the use of daily cumulative precipitation as an indicator for calculating the
390 return period or evaluating the degree of disaster risk is equivalent to the estimation of
391 the univariate return period in scenarios with a duration of less than 24 h, which is a
392 significant limitation for objectively evaluating the degree of disaster risk of heavy
393 precipitation in Shandong. Considering that the short duration of most heavy
394 precipitation events in Shandong means that there will be a significant difference
395 between the estimated univariate and joint return periods of heavy precipitation events,
396 the previous indicator values calculated from daily precipitation will seriously
397 underestimate the hazardousness and disaster-causing degree of short-duration heavy



398 precipitation processes.^(2,3) The joint return period of heavy precipitation estimated
399 using the Copula joint distribution describes the dependence between the duration of
400 heavy precipitation and the amount of precipitation. The estimation method takes the
401 intensity of heavy precipitation into account, which can more objectively characterize
402 the frequency information of the heavy precipitation scenarios of different calendars,
403 and thus is conducive to a more reasonable description of the risk of the heavy
404 precipitation-causing factors in different scenarios.

405

406 **4.4 Characteristics of the spatial distribution of multi-scenario heavy**

407 **precipitation return periods**

408

409 For the scenario of heavy precipitation events with precipitation exceeding 50
410 mm, comparing the spatial distribution of the joint and univariate return periods under
411 the scenario of duration less than the 8-h threshold in Shandong (Fig. 7), the heavy
412 precipitation of the above scenario may cause disasters such as mudslides, urban
413 flooding, and landslides, etc. Analyzing the joint return period of the above scenario
414 has positive significance for the prevention and mitigation of heavy precipitation and
415 the construction of the urban drainage system, and it will provide a basis for
416 decision-making. The analysis of the joint recurrence period of the above scenarios is
417 of positive significance for preventing and mitigating heavy precipitation and
418 constructing urban drainage systems. From Fig. 8, it can be seen that the spatial
419 distribution of the joint recurrence period of heavy precipitation shows different
420 spatial distribution characteristics with the change of duration thresholds. However,



421 the spatial distribution of the univariate recurrence period with different duration
422 thresholds is nearly the same. For the scenarios with precipitation exceeding 50 mm
423 and duration thresholds lower than 1 h, the high values of the spatial distribution of
424 the joint recurrence period are roughly concentrated in the central, eastern, and
425 southern regions, and the frequency of heavy precipitation in the western region is
426 relatively low; with the gradual increase of the precipitation duration, the area of high
427 values of the joint recurrence period is gradually narrowed down to the eastern region,
428 and the area of low values of the joint recurrence period is continuously expanding in
429 the western part of Shandong. The spatial distribution of scenarios with precipitation
430 exceeding 50 mm and a duration threshold of 8 h is similar to that of 3 h, indicating
431 that most heavy precipitation in samples with precipitation durations of up to 8 h
432 lasted less than 3 h. The spatial distribution of scenarios with precipitation exceeding
433 50 mm does not differ significantly from those with a duration threshold of 8 h.
434 However, the spatial distribution of the joint return period (JRP) is significantly
435 different for the scenario with a threshold of 1 h compared with the scenario with a
436 threshold of 6 h. The spatial distribution of the JRP is highly uneven. The high values
437 of the JRP are concentrated in the south, and the east of the country, which suggests
438 that the heavy precipitation events in the above areas occur more frequently within 1 h,
439 and the risk of disaster is correspondingly higher. The spatial distribution of the joint
440 return period also indicates the impacts of the short-term heavy precipitation events
441 (Zheng et al., 2014). The above differences in the spatial distribution of the return
442 period scenarios with different precipitation duration thresholds indicate that



443 analyzing the risk of heavy precipitation in combination with the duration and amount
444 of precipitation can more objectively characterize the spatial distribution of the
445 intensity and frequency of the risk factors of heavy precipitation in different scenarios,
446 and provide a reference basis for decision-making on how to cope with the disaster
447 risk of heavy precipitation events with different durations in Shandong.

448 Scientific estimation of the precipitation amount during the return period of heavy
449 precipitation for different scenarios is an essential reference for urban construction
450 and planning of drainage systems. In this section, the Copula joint distribution is used
451 to estimate the precipitation thresholds for the return periods of 10 a and 30 a, and the
452 spatial distribution characteristics of precipitation for the above two scenarios are
453 given, which are used as important references to analyze the hazardousness of heavy
454 precipitation processes. In both scenarios, with a return period of 10 a (Fig. 8a) and 30
455 a (Fig. 8b), the precipitation thresholds gradually increase along with the extension of
456 the precipitation duration. The increase in precipitation is more pronounced in the
457 scenario with a return period of 30 a compared to the scenario with a return period of
458 10 a (Fig. 8a). For the scenario with a return period of 30 a, the precipitation threshold
459 gradually widens in the southeastern mountain region with the increase in the duration
460 of heavy precipitation (Fig. 8b), and is expected to exceed 300 mm. The analysis of
461 the above results shows pronounced regional differences in the risk of disasters
462 caused by different scenarios of heavy precipitation events, in which the risk of a
463 once-in-thirty-years heavy precipitation event is higher in areas such as the southeast
464 and east of the mountain. It is recommended that the construction of urban stormwater



465 systems and planning flood prevention and mitigation in the above areas should be
466 prioritized.

467

468 **5.CONCLUSION AND DISCUSSIONS**

469

470 This paper introduces the method of establishing the Copula binary joint
471 distribution of heavy precipitation duration and precipitation amount based on hourly
472 heavy precipitation data, calculating the joint return period (JRP), which can reflect
473 the risk of disasters caused by heavy precipitation events and statistically evaluating
474 the degree of disasters caused by heavy precipitation of the same scenario in the
475 mountains based on the JRP. The results show that the Copula joint distribution can be
476 used to effectively characterize the dependence structure of heavy precipitation
477 duration and precipitation amount and describe the frequency information under
478 different ephemeral heavy precipitation scenarios, especially the impacts brought by
479 short-duration heavy precipitation. Compared with the previous approach of relying
480 on univariate estimation of the return period (Utsumi N et al., 2022; Wang et al.,
481 2023), the two-dimensional intensity and frequency information of heavy
482 precipitation-causing factors can be more reasonably portrayed to provide a scientific
483 basis for the prevention and mitigation planning of heavy precipitation events and
484 their disaster risk management.

485 The observed duration of heavy precipitation and precipitation amount are highly
486 correlated, with Kendall rank correlation coefficients between precipitation amount



487 and precipitation duration ranging from 0.4 to 0.8 (having passed the 0.01
488 significance level test), and the precipitation amount increases with the duration,
489 showing a clear positive correlation with a correlation coefficient of 0.62. From the
490 spatial distribution of Kendall correlation coefficients between precipitation duration
491 and precipitation (Fig. 9a), it can be seen that the correlation is more pronounced in
492 the coastal and southern regions. As seen from Fig. 9, the heavy precipitation in
493 Shandong in the past 30 years is concentrated in the central and southern parts of the
494 country, and the frequency of occurrence is about 157 times on average. Overall, there
495 is a significant dependence between the precipitation amount and the duration of
496 heavy precipitation in Shandong. This is suitable for calculating the return period by
497 constructing a joint distribution through the Copula function.

498 Due to the short duration and high intensity of heavy precipitation in the study
499 area in the past 30 years, most heavy precipitation lasts for less than 3 h. In the past,
500 the reproduction period estimated by daily precipitation will underestimate the
501 disaster risk of short-term heavy precipitation (Cheng et al., 2022; Vergni et al., 2015;
502 Ummul et al., 2014). The joint reproduction period estimated by using hourly rainfall
503 data is more accurate. The disaster risk of heavy precipitation in different scenarios
504 can be recognized based on the Copula joint distribution, useful in disaster risk
505 assessment and urban defense engineering construction. These different scenarios are
506 very useful in disaster risk assessment and urban defense engineering construction
507 and are of great significance in disaster prevention and mitigation planning and
508 disaster risk management.



509 In the Shandong region of China, the joint return period of heavy precipitation
510 estimated by the Copula joint distribution has noticeable spatial differences with the
511 extension of the precipitation time. The scenario of one in 10 years has a higher
512 concentration of precipitation in the southeastern and eastern parts of the mountain,
513 especially in 30 years of heavy precipitation, which has a very high risk of disaster in
514 the southeastern and eastern parts of the mountain. It is recommended to focus on
515 considering the urban stormwater system and the flood disaster prevention project in
516 this region to Prevent economic and other losses.

517 The existing studies show apparent differences in the characteristics of changes in
518 the frequency of heavy precipitation in different regions. In this paper, the
519 hourly-scale precipitation samples of the last 30 years are selected, which mainly
520 characterize the disaster-causing situation of heavy precipitation on the hourly scale
521 and are suitable for reflecting the extreme precipitation situation. If precipitation
522 events at other time scales are selected, the hazard identification of heavy
523 precipitation events will change. Meanwhile, in the identification and analysis of
524 heavy precipitation events based on the Copula function, there is no uniform
525 regulation for threshold selection, which makes it easy to reduce the accuracy of
526 identifying extreme events so that the threshold setting method can be further
527 optimized.

528 In this paper, only two feature variables of heavy precipitation duration and heavy
529 precipitation amount are combined, and the structure of the multivariate joint function
530 will be more complicated with the increase of the feature variables of heavy



531 precipitation events. The characteristics of heavy precipitation have a solid sensitivity
532 to time and space, and the spatial and temporal characteristics of different regions
533 make the Copula function time-varying for applying heavy precipitation. Therefore,
534 future research will focus on solid precipitation indicator selection, threshold
535 optimization, Copula multidimensional eigenvariable analysis, and time-varying
536 exploration.

537 In recent years, some scholars have found that the frequency and intensity of
538 natural disasters in recent years have been characterized by a significant increase in
539 frequency and intensity, accompanied by the occurrence of multiple types of disasters,
540 and the law of occurrence of natural disasters and sound factors have become more
541 complex. A more scientific analysis of the probability of extreme weather and climate
542 events will help decision-makers take measures more quickly and effectively to
543 prevent, reduce, or avoid the impacts and losses caused by disasters. As uncertainties
544 increase, the analysis of natural disasters needs to be more rationalized. One of the
545 advantages of using the Copula function is that it can be extended to n-latitude frames.
546 However, the current research and application of the Copula function is mainly
547 limited to two-dimensional; with the advancement of computer technology and the
548 complexity of the research problems, the application of three-dimensional and above
549 Copula function and the accompanying problems of parameter estimation and the
550 choice of the function type need to be further researched. Therefore, the Copula
551 function has great potential in the risk assessment of natural disasters caused by
552 multiple factors.



553

554 **Conflict of Interest:**The authors declare that they have no known competing
555 financial interests or personal relationships that could have appeared to influence the
556 work reported in this paper.

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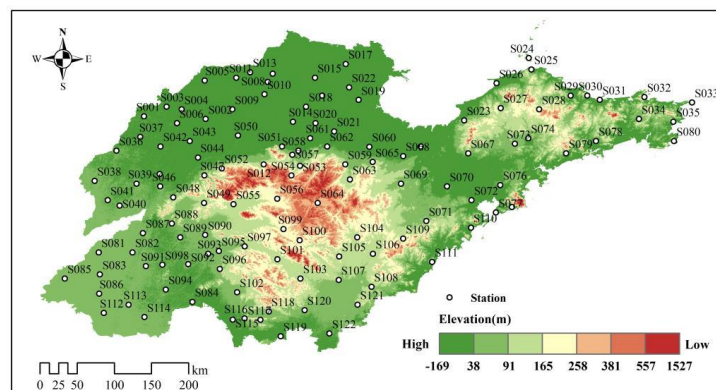
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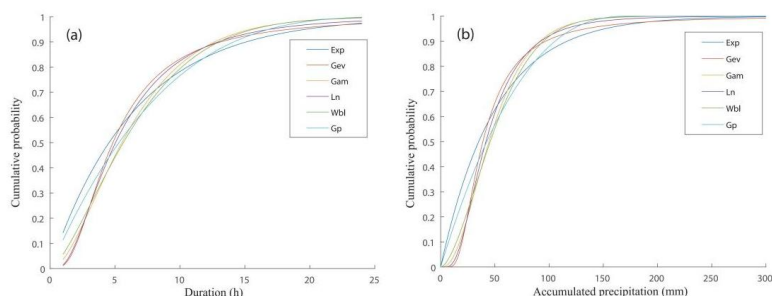


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634 **Figure 1.** Spatial distribution of sites and topographic height distribution in
635 Shandong.



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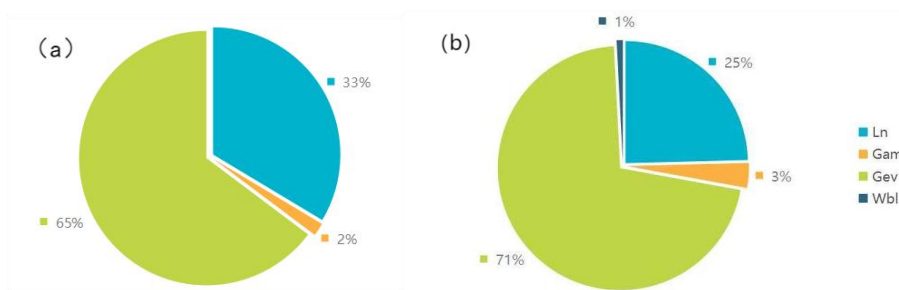


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Figure 2. Candidate Marginal Distribution Fitting for Duration (a) and Duration (b) of Heavy Precipitation at Laoshan Station, Qingdao, Shandong, China



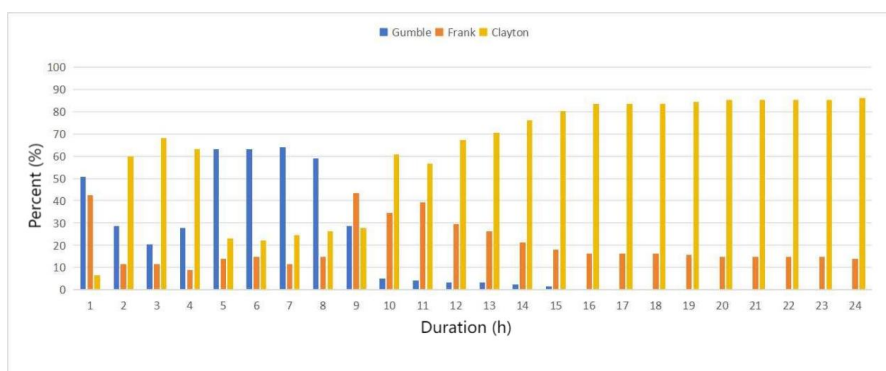
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Figure 3. Percentage of optimal marginal distribution of heavy precipitation precipitation (a) and duration (b) at 122 observation stations in Shandong Province



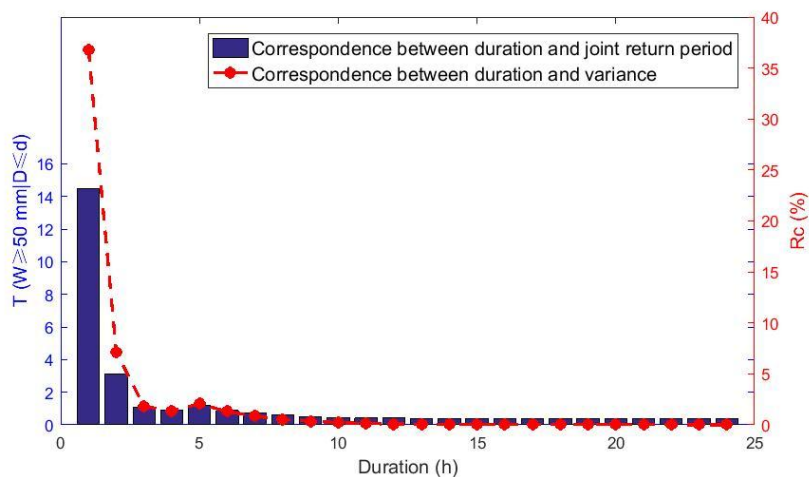
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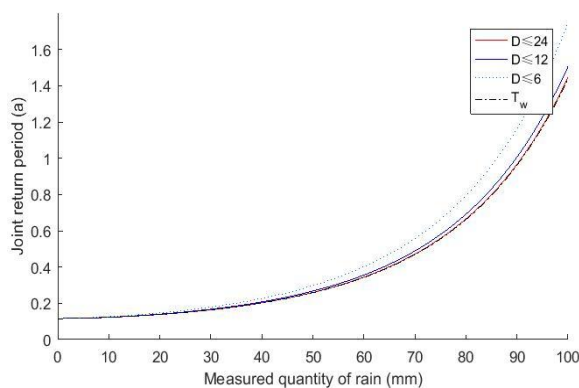
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Figure 4. Percentage of types of best-fit Copula joint distribution functions for different time-lengths of intense precipitation



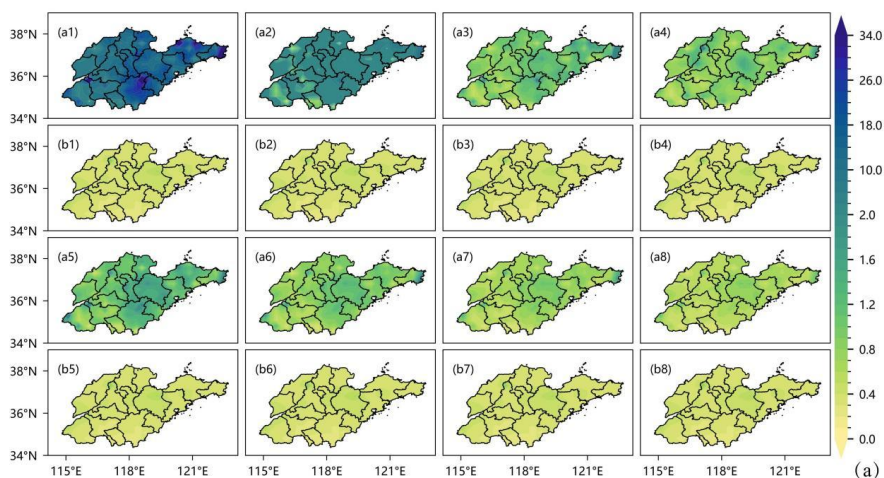
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Figure 5. Duration of heavy precipitation in Shandong in relation to the conditional return period (a) and the rate of difference R_c (b)



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Figure 6. Comparison of joint and univariate return periods for different heavy precipitation durations at Laoshan station



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657 **Figure 7.** Spatial distribution of process precipitation ≥ 50 mm for durations ≤ 1

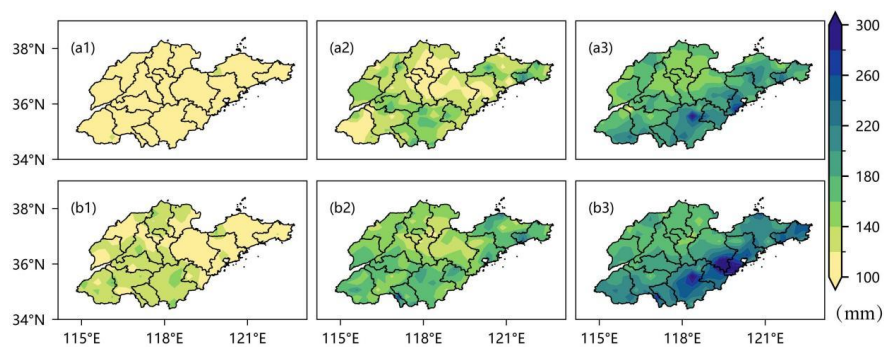
658 h (a1,b1), durations ≤ 2 h (a2,b2), durations ≤ 3 h (a3,b3), durations ≤ 4 h

659 (a4,b4), durations ≤ 5 h (a5,b5), durations ≤ 6 h (a6,b6), durations ≤ 7 h (a7,b7)

660 and durations ≤ 8 h (a8, b8) the spatial distribution of joint and univariate return

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periods of heavy precipitation



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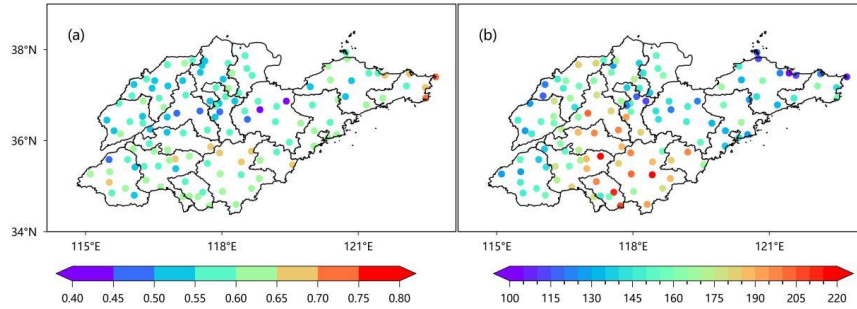
663 **Figure 8.** Precipitation (mm) thresholds (a1, b1 duration ≤ 6 h, a2, b2 duration \leq

664 12h, a3, b3 duration ≤ 24 h) for 1 in 10 years (a1, a2, a3) and 1 in 30 years (b1, b2,

665

b3) joint return periods

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668 **Figure 9.** Spatial distribution of kendall correlation coefficients (a) and number of

669 heavy precipitation (b) between precipitation duration and precipitation, 1990-2023

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671 **Table 1.** Three Candidate Copula Distribution Functions

Copula style	distribution function	parameters
Frank	$C_{Frank}(u, v) = -\frac{1}{\theta} \ln \left(1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{(e^{-\theta} - 1)} \right)$	$\theta \in (-\infty, \infty) \setminus \{0\}$
Gumble	$C_{Gumble}(u, v) = \exp \left(- \left[(-\ln u)^{\frac{1}{\theta}} + (-\ln v)^{\frac{1}{\theta}} \right]^{\theta} \right)$	$\theta \in (0, 1]$
Clayton	$C_{clayton}(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{-\frac{1}{\theta}}$	$\theta \in (0, \infty)$

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674 **Table 2.** Six marginal distribution functions

Marginal distribution type	Probability Density Function (PDF)	parameters
Generalised Extreme Value (Gev)	$f_{GEV}(x) = \frac{1}{\sigma} e^{-\left(1 + \omega \frac{x-u}{\sigma}\right)^{-\frac{1}{\omega}}} \left(1 + \omega \frac{x-u}{\sigma}\right)^{-1 - \frac{1}{\omega}}$	ω is the shape parameter, u is the position parameter, σ is the scale parameter ($1 + \omega \frac{x-u}{\sigma} > 0$)



		$\omega \neq 0^1 + \omega \frac{x-u}{\sigma} > 0, \omega \neq 0$
Lognormal (Ln)	$f_{LN}(x) = \frac{1}{xv\sqrt{2\pi}} e^{-\frac{(\ln x - u)^2}{2v^2}}, (x > 0)$	u is the mean($-\infty < u < +\infty$), v is the standard deviation
Gamma (Gam)	$f_{Gam}(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}}, (x > 0)$	α is the shape parameter, β is the scale parameter
Weibull (Wbl)	$f_{Wbl}(x) = \frac{\beta}{\alpha-\beta} x^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^{-\beta}}, (x \geq 0)$	α is the shape parameter, β is the scale parameter
Exponential (Exp)	$f_{Exp}(x) = \frac{e^{-\frac{x}{u}}}{u}$	u is the mean($0 < u < +\infty$)
Generalised Pareto (Gp)	$f_{Gp}(x) = \frac{1}{\sigma} \left(1 - \omega \frac{x-u}{\sigma}\right)^\omega$	ω is the shape parameter, u is the position parameter, σ is the scale parameter

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