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**Abstract** Quantifying the contributions of climate change (CC) and human activities (HA) to streamflow alteration is significant for effective water resources management. However, numerous studies fail to differentiate the individual impacts of various HA on streamflow. In this study, a comprehensive streamflow attribution framework that incorporates climate, vegetation, and water withdrawal (WW) was proposed. In this framework, traditional streamflow attribution methods such as statistical analysis (Double Mass Curve and Slope Change Ratio of Accumulative Quantity), elasticity (Budyko), and modeling simulation (Variable Infiltration Capacity and Long Short-term Memory) are employed to separate the influence of meteorological factors (MF) on streamflow. Subsequently, the impacts of WW on streamflow are assessed using global WW data. The Residual Analysis method is utilized to quantify the effects of vegetation alteration caused by both CC (Lcc) and HA (Lha) on streamflow alteration. To demonstrate the applicability of our proposed framework, two stations, Xianyang and Huaxian, located within the Weihe River Basin in Northwest China were selected as the case study area. The results demonstrated that compared to the baseline period (1961–1990), the average contributions of MF, Lcc, Lha, and WW to streamflow reduction during the variation periods (1991–2019) were as follows: for the Xianyang station, 26.0%, 13.5%, 30.9%, and 29.6% respectively; and for the Huaxian station, 28.9%, 5.5%, 17.7%, and 47.9% respectively. Additionally, during the variation periods, the contributions of CC and HA to vegetation variation were 30.5% and 69.5% respectively in Xianyang, and 23.7% and 76.3% respectively in Huaxian. The framework developed herein also provides a solution for quantifying the indirect effects of CC on streamflow through vegetation.

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**Keywords (separated by '-')** Climate change - Vegetation change - Attribution analysis - Residual analysis - Water withdrawal

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**Footnote Information**

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# 1 A Complementary Streamflow Attribution Framework 2 Coupled Climate, Vegetation and Water Withdrawal

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## 7 Abstract

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28 also provides a solution for quantifying the indirect effects of CC on streamflow through  
29 vegetation.

30 **Keywords** Climate change · Vegetation change · Attribution analysis · Residual analysis ·  
31 Water withdrawal

## 32 1 Introduction

33 Streamflow plays a crucial role in the overall water resources system (Grill et al. 2019).  
34 However, the streamflow of many rivers worldwide has undergone substantial changes  
35 since the mid-20th century as a result of climate change (CC) and human activities (HA)  
36 (Rani and Sreekesh 2019; Melo et al. 2023). On the one hand, CC, particularly varia-  
37 tions in precipitation patterns, directly impacts the trends of streamflow (Ahmed et al.  
38 2022; Gholami and Sahour 2022). On the other hand, HA, including land cover changes  
39 and water withdrawals (WW), exert direct or indirect influences on streamflow (Krajew-  
40 ski et al. 2021; Zhu et al. 2021). Consequently, accurately quantifying and attributing the  
41 contributions of climate, vegetation, and WW changes to alteration in streamflow is crucial  
42 for developing effective water resources management strategies (Alehu and Bitana 2023;  
43 Wang et al. 2023).

44 Currently, various approaches have been employed to differentiate the contributions of  
45 CC and HA to streamflow alteration, including statistical analysis, elasticity, and modeling  
46 simulation methods (Sharifi et al. 2021). Statistical analysis approaches, such as the dou-  
47 ble mass curve (DMC) and slope change ratio of accumulative quantity (SCRAQ), utilize  
48 statistical techniques to isolate the influence of meteorological factors (MF), specifically  
49 precipitation, on streamflow as an indicator of CC-induced streamflow alteration (Wang  
50 et al. 2012). Elasticity approaches are primarily based on Budyko's hypotheses, using sen-  
51 sitivity coefficients of MF to streamflow and catchment-specific parameter  $n$  to isolate the  
52 impacts of CC and HA on streamflow (Sharifi et al. 2021). Modeling simulation meth-  
53 ods involve hydrological models like the Variable Infiltration Capacity (VIC) model and  
54 machine learning models like long short-term memory (LSTM) that can simulate natural  
55 streamflow (Sahour et al. 2021; Zhang et al. 2022). By comparing the simulated stream-  
56 flow with observed streamflow, these models can differentiate the contributions of CC and  
57 HA to streamflow alteration, assuming that the difference between observed and natural  
58 streamflow is attributable to HA (Jiang et al. 2019; Gholami and Khaleghi 2021).

59 Different methods or perspectives may exhibit disparities or contradictions in the same  
60 area (Luan et al. 2021). For instance, Swain et al. (2021), employing three complemen-  
61 tary approaches, discovered that the DMC and SCRAQ methods alleviate the effects of CC  
62 compared to hydrological models. Sharifi et al. (2021), using nine methods, indicated that  
63 non-parametric attribution methods are unsuitable for streamflow attribution in the Ghaleh-  
64 Shahrokh watershed when compared to Budyko and hydrological model methods. There-  
65 fore, an increasing number of researchers are adopting multiple combination approaches  
66 to isolate the contributions of CC and HA to streamflow alteration in order to mitigate  
67 the uncertainty associated with a single method (Swain et al. 2021). However, there is a  
68 lack of research regarding the differentiation of the impacts of different HA on stream-  
69 flow. Currently, the Budyko method and the reduction streamflow method are utilized to  
70 differentiate the effects of land cover changes and WW on streamflow alteration (Li et al.  
71 2022). For example, Bao et al. (2021) employed the disparity between natural streamflow  
72 restored by water resource evaluation and natural streamflow restored by a hydrological  
73 model to represent the impact of land cover changes on streamflow. Nevertheless, this  
74 method failed to consider WW and land cover data. Therefore, a complementary stream-  
75 flow attribution framework coupled climate, vegetation, and WW was proposed. In this  
76 framework, the impacts of MF on streamflow were separated using traditional streamflow  
77 attribution methods such as statistical analysis, elasticity, and modeling simulation. Subse-  
78 quently, the impacts of WW on streamflow were distinguished based on global WW data.

79 The remaining impacts were attributed to land cover changes. Finally, the effect of CC and HA on  
 80 HA on streamflow through land cover was substituted with the effect of CC and HA on  
 81 vegetation changes using the residual analysis (RA) method. Moreover, the RA method,  
 82 which predicts the changing trend of multi-grid climate variables, is widely employed to  
 83 attribute alterations in vegetation's Normalized Difference Vegetation Index (NDVI) and  
 84 determine the contributions of CC and HA to vegetation changes (Zhou et al. 2022).

85 In this study, a complementary streamflow attribution framework that integrates cli-  
 86 mate, vegetation, and WW was proposed, which can assess the effects of MF, vegeta-  
 87 tion alteration caused by CC (Lcc), vegetation alteration caused by HA (Lha) and WW  
 88 on streamflow. The Weihe River Basin (WRB) in Northwest China, a typical area with a  
 89 heavy hydrological alteration, was selected as the case study area to perform the comple-  
 90 mentary streamflow attribution framework. We aimed (1) to isolate the contributions of  
 91 CC and HA on streamflow and vegetation alteration, and (2) to quantify the impacts of cli-  
 92 mate, vegetation and WW alterations on streamflow and characterize the response between  
 93 streamflow and vegetation.

94 **2 Material and Methods**

95 In this section, a comprehensive streamflow attribution framework that integrates climate,  
 96 vegetation, and WW was proposed (Fig. 1). The framework consists of four steps. The first  
 97 step involves determining baseline and variation periods using the Pettitt test (P-test) and the  
 98 Accumulative Anomaly Method (AAM), as previously described by Wang et al. (2012). The  
 99 second step focuses on separating the contributions of CC and HA to streamflow and vegeta-  
 100 tion alterations. To achieve this, traditional approaches such as statistical analysis (DMC and  
 101 SCRAQ), elasticity (Budyko), and modeling simulation (VIC and LSTM) are used for stream-  
 102 flow attribution caused by MF. Additionally, the RA method is utilized for attributing changes  
 103 in vegetation. Third, there are three schemes for streamflow attribution that incorporate

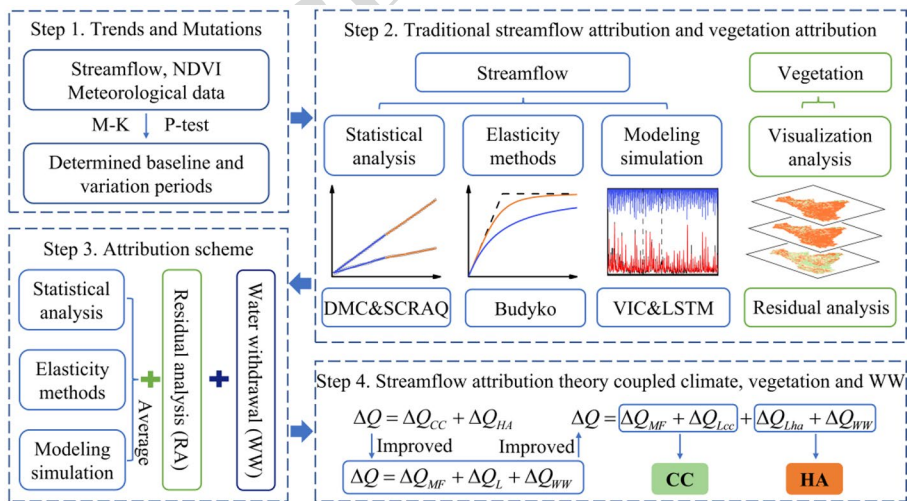


Fig. 1 Proposed complementary streamflow attribution framework coupled climate, vegetation and water withdrawal

104 climate, vegetation, and WW. These schemes include: (1) coupling statistical analysis, RA,  
105 and WW; (2) coupling elasticity methods, RA, and WW; and (3) coupling modeling simula-  
106 tion, RA, and WW. By averaging the results obtained from the three schemes, the findings  
107 of this study can effectively reduce uncertainty and enhance the robustness of the analysis.  
108 Finally, an improved streamflow attribution method coupled climate, vegetation and WW was  
109 proposed.

AQ1

## 110 2.1 Traditional Streamflow Attribution

### 111 2.1.1 Statistical Analysis

112 The DMC and SCRAQ are two popular linear statistical analysis methods used to separate the  
113 influence of precipitation on streamflow, representing the contribution of MF to streamflow  
114 alterations (Wang et al. 2012 and Yang et al. 2018).

### 115 2.1.2 Elasticity Method

116 The long-term water balance is as below (Swain et al. 2021):

$$117 \quad P = E + Q + \Delta S \quad (1)$$

118 where  $P$ ,  $E$ , and  $Q$ , are precipitation, actual evapotranspiration, streamflow, and  $\Delta S$  is the  
119 alteration in water storage which can be assumed to be zero on a multi-year scale. The arid-  
120 ity index ( $\varphi$ ) and evaporative index ( $F(\varphi)$ ) are respectively the ratios of the potential evapo-  
121 transpiration ( $E_p$ ) and actual evapotranspiration ( $E$ ) to precipitation as follow:

$$123 \quad \varphi = E_p/P \quad (2)$$

$$125 \quad F(\varphi) = E/P \quad (3)$$

127 The mathematical equations based on Budyko hypotheses have been developed to account  
128 for streamflow alteration:

$$129 \quad Q = P - E = P - \frac{E_p P}{(P^n + E_p^n)^{1/n}} \quad (4)$$

130 where  $E_p$  is potential evapotranspiration, and  $n$  is the catchment-specific parameter, such as  
131 soil properties, slope, and vegetation cover. The elasticity of streamflow to  $P$  and  $E_p$  can be  
132 computed as (Luan et al. 2021):

$$134 \quad \Delta Q_{CC} = \frac{\partial Q}{\partial P} \Delta P + \frac{\partial Q}{\partial E_p} \Delta E_p \quad (5)$$

$$136 \quad \frac{\partial Q}{\partial P} = 1 - \frac{E}{P} \left( \frac{E_p^n}{P^n + E_p^n} \right) \quad (6)$$

$$138 \quad \frac{\partial Q}{\partial E_p} = -\frac{E}{E_p} \left( \frac{P^n}{P^n + E_p^n} \right) \quad (7)$$

139

$$\Delta Q_{HA} = \Delta Q - \Delta Q_{CC} \quad (8)$$

140

141

142 where  $\Delta Q_{HA}$  and  $\Delta Q_{CC}$  are the streamflow alteration caused by CC and HA alteration.

### 143 2.1.3 Modeling Simulation

144 The VIC model is a semi-distributed hydrological model and has been applied in daily-  
 145 scale hydrological simulation. More model parameters and details can be found in Jiang  
 146 et al. (2022). The LSTM is an improved recurrent neural network. The information can be  
 147 stored in an additional cell state, which enables LSTM more advantage for sequential data  
 148 in machine learning (Zhang et al. 2022). The Nash–Sutcliffe efficiency coefficient (NSE) is  
 149 used to optimize model parameters.

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{sim}(i) - Q_{obs}(i))^2}{\sum_{i=1}^n (Q_{sim}(i) - \bar{Q}_{obs})^2} \quad (9)$$

150

151 where  $Q_{obs}(i)$ ,  $Q_{sim}(i)$ , and  $\bar{Q}_{obs}$  are the observed, simulated, and mean observed stream-  
 152 flow, respectively;  $m$  is the number of data points.

153 The VIC and LSTM can separate the contributions of CC and HA on streamflow  
 154 through the simulated-observed comparison method which can assume that difference  
 155 between observed streamflow and natural streamflow was due to HA.

$$\Delta Q = \Delta Q_{HA} + \Delta Q_{CC} = \bar{Q}_{obs,var} - \bar{Q}_{obs,base} \quad (10)$$

157

158

$$\Delta Q_{CC} = \bar{Q}_{sim,var} - \bar{Q}_{sim,base} \quad (11)$$

159

160

$$\Delta Q_{HA} = \Delta Q - \Delta Q_{CC} = (\bar{Q}_{obs,var} - \bar{Q}_{obs,base}) - (\bar{Q}_{sim,var} - \bar{Q}_{sim,base}) \quad (12)$$

161

162

163 where  $\bar{Q}_{obs,var}$  and  $\bar{Q}_{obs,base}$  are the average streamflow in the variation period and the base-  
 164 line period.  $\bar{Q}_{sim,var}$  and  $\bar{Q}_{sim,base}$  are the average simulated streamflow by VIC and LSTM in  
 165 the variation period and the baseline period (Jiang et al. 2019).

### 166 2.2 Vegetation Attribution

167 In this study, the RA approach was employed to isolate the impacts of CC and HA on **AQ2**  
 168 vegetation alterations. The underlying assumption is that HA's impact on vegetation can  
 169 be captured by the unexplained variations in the model. To achieve this, precipitation and  
 170 temperature were selected as the primary MF influencing vegetation. Previous studies have  
 171 demonstrated that multiple linear regression models can effectively capture the vegetation  
 172 response to MF. The method utilized in this study consists of four main steps (Zhou et al.  
 173 2022), which are as follows:

- 174 1. A multiple linear regression model among the maximum annual NDVI, average annual  
 175 precipitation (P) and average annual temperature (T) was established.

$$NDVI_{CC} = a \times T + b \times P + c \quad (13)$$

176

177



178 where  $NDVI_{CC}$  represents the effect of CC on vegetation. The  $a$  and  $b$  are regression coef-  
179 ficients and  $c$  is the intercept.

180 2. The  $NDVI_{obs}$  is interannual trend rate of NDVI.

$$181 \quad NDVI_{obs} = \frac{n \sum_{i=1}^n (i \times NDVI_i) - \sum_{i=1}^n i \sum_{i=1}^n NDVI_i}{n \sum_{i=1}^n i^2 - \sum_{i=1}^n i} \quad (14)$$

182 where the “ $i$ ” is the time variable (year), equal to an integer from 1 to  $n$  and the “ $n$ ” is the  
183 number of years in the research period.  $NDVI_i$  is the maximum NDVI at  $i$  year.

185 3. The difference between the predicted ( $NDVI_{CC}$ ) and observed NDVI ( $NDVI_{obs}$ ) is the  
186 residual, which indicates the response of vegetation to HA ( $NDVI_{HA}$ ).

187  $NDVI_{HA} = NDVI_{obs} - NDVI_{CC}$  (15)  
188 4. The contributions of CC ( $\eta_{CC}$ ) and HA ( $\eta_{HA}$ ) to vegetation alteration can be calculated  
189 as.

$$190 \quad \eta_{CC} = NDVI_{CC} / NDVI_{obs} \quad (16)$$

$$191 \quad \eta_{HA} = NDVI_{HA} / NDVI_{obs} \quad (17)$$

### 194 2.3 Improved Streamflow Attribution

195 The traditional streamflow attribution hypothesis is that the streamflow alteration is caused by  
196 MF and HA.

$$197 \quad \Delta Q = \Delta Q_{CC} + \Delta Q_{HA} = \Delta Q_{MF} + \Delta Q_{HA} \quad (31)$$

198 where  $\Delta Q$ ,  $\Delta Q_{MF}$ , and  $\Delta Q_{HA}$  are streamflow alteration, and streamflow alteration caused  
200 by MF and HA.

201 It can be further assumed that the streamflow alteration is caused by MF, land use and WW.

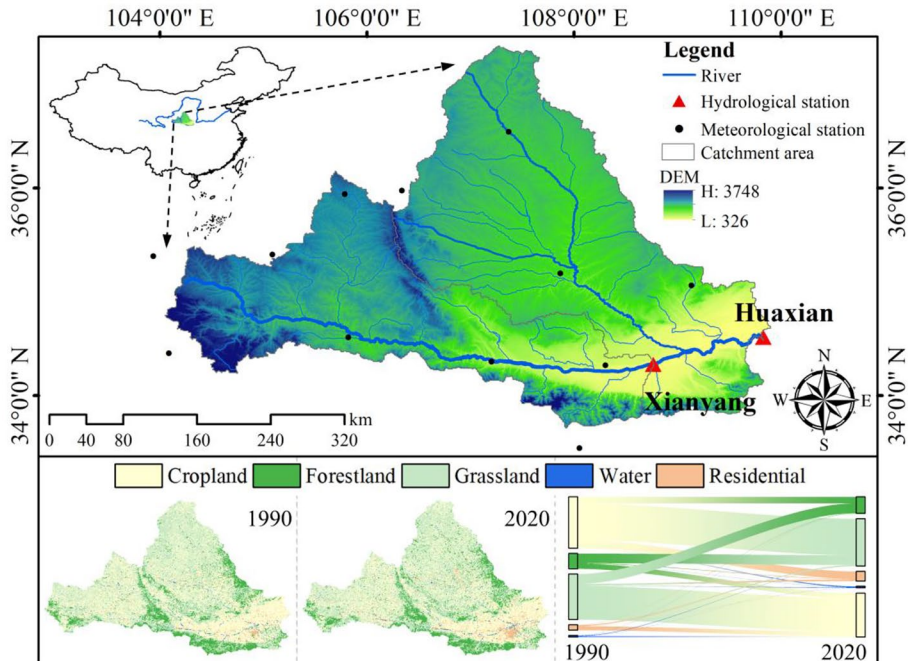
$$202 \quad \Delta Q = \Delta Q_{MF} + \Delta Q_L + \Delta Q_{WW} \quad (32)$$

203 where  $\Delta Q_L$  and  $\Delta Q_{WW}$  are streamflow alteration caused by land use and WW.

205 Here the effect of CC and HA on streamflow through land cover was replaced by the effect  
206 of CC and HA on vegetation change. Therefore, the new streamflow attribution can be further  
207 written as:

$$208 \quad \Delta Q = \Delta Q_{MF} + \Delta Q_{Lcc} + \Delta Q_{Lha} + \Delta Q_{WW} \quad (33)$$

209 where  $\Delta Q_{Lcc}$  and  $\Delta Q_{Lha}$  are streamflow alteration caused by vegetation alteration caused by  
210 CC and HA.  $\Delta Q_{MF}$  and  $\Delta Q_{Lcc}$  represent the impact of CC on streamflow alteration.  $\Delta Q_{Lha}$   
212 and  $\Delta Q_{WW}$  represent the impact of HA on streamflow alteration.



**Fig. 2** Location of the Weihe River Basin, the hydrological and meteorological stations, and land use alteration from 1990 to 2020

**Table 1** Data used in this study

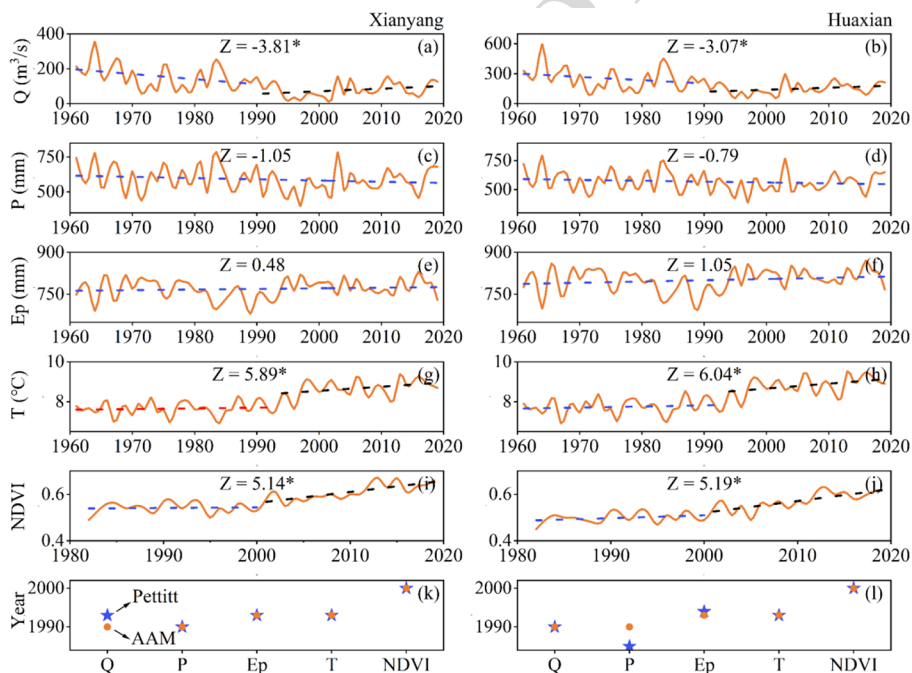
Data	Time	source
Daily streamflow records	1961–2019	Yellow River Conservancy Commission
Daily meteorological records	1961–2019	China Meteorological Data Sharing Service System
NDVI	1982–2019	National Earth System Science Data Center
WW	1961–2019	Yan et al. (2022) and Yellow River Resource Bulletin
Land cover	1990/2000	Resources and Environmental Science and Data Center, Chinese Academy of Sciences
Global 1-km land cover classification product	2000	University of Maryland

## 213 2.4 Study Area and Data

214 The WRB belongs to the Loess Plateau with an area of  $10.6 \times 10^4 \text{ km}^2$ , which is the largest  
 215 tributary of the Yellow River. Two hydrologic stations (Xianyang and Huaxian) (Fig. 2),  
 216 were selected as the controlling stations. Based on the observed hydro-meteorological  
 217 records from 1961 to 2019, the mean annual air temperature and precipitation are 9.4  
 218 °C and 569.1 mm, respectively. Besides, HA have altered the underlying surface of the  
 219 WRB by returning cropland to forestland and grassland (Luan et al. 2021). Moreover, spe-  
 220 cific data can be found in Table 1.

221 **3 Results**222 **3.1 Trend and Mutation Analysis**

223 The results obtained from M–K and linear regression conducted in the WRB indi-  
 224 cate that there is no significant trend in precipitation and potential evapotranspiration  
 225 (Fig. 3c–f). However, a significant downward trend is evident in streamflow (Fig. 3a,  
 226 b), while temperature and NDVI (Fig. 3g–j) show a significant upward trend ( $P < 0.01$ ).  
 227 There were distinct mutations in streamflow, temperature, and NDVI in 1990, 1993,  
 228 and 2000, respectively, at the Xianyang and Huaxian stations (Fig. 3k, l). It is worth  
 229 mentioning that 1990 marked a prominent turning point for streamflow (Fig. 3a, b).  
 230 Furthermore, HA in the WRB have experienced significant increases since 1990 (Liu  
 231 et al. 2022). Therefore, 1990 was identified as the mutation, with the baseline period  
 232 from 1961 to 1990 and the variation period from 1991 to 2019. Similar research find-  
 233 ings have been reached by Liu et al. (2022) using different analysis methods. Moreo-  
 234 ver, within the variation period, the HA exhibits variations across different stages (Luan  
 235 et al. 2021). Consequently, the variation period was segmented into three stages: period  
 236 I (1991–2000), period II (2000–2010), and period III (2010–2019).



**Fig. 3** The trends and mutations of streamflow (Q), precipitation (P), potential evapotranspiration (Ep), temperature (T), and NDVI in the Xianyang and Huaxian stations. (a–j): trends of Mann–Kendall (M–K) and linear regression; \* Significant trends at 1% level; k–l: mutations of Pettitt test (P-test) and Accumulative Anomaly Method (AAM)

237 **3.2 Relative Contribution Based on Traditional Hydrological Methods**

238 **3.2.1 Model Parameters**

239 In the DMC method (Fig. 4a, b), the slopes for the Xianyang and Huaxian stations during  
 240 the baseline period were 0.15 and 0.11, respectively, which decreased to 0.08 and  
 241 0.07, respectively, during the variation period. In the SCRAQ method (Fig. 4c, d), the  
 242 slope for precipitation and streamflow at the Xianyang station was 0.61 and 0.14 during  
 243 the baseline period, respectively, which decreased to 0.57 and 0.08 during the variation  
 244 period. Similarly, at the Huaxian station, the slope for precipitation and streamflow was  
 245 0.58 and 0.23 during the baseline period, respectively, which decreased to 0.55 and 0.15  
 246 during the variation period.

247 The calibration of the Budyko using a single parameter in the WRB during the base-  
 248 line and variation periods showed a strong agreement between the estimated actual  
 249 evapotranspiration and the values derived from the water balance equation. The NSE  
 250 values exceeded 0.81, indicating that the parameters of the Budyko equation success-  
 251 fully captured the characteristics of the catchments. The parameter  $n$  for the Xianyang  
 252 catchment were 2.87 and 3.64 in the baseline and variation periods, respectively, which  
 253 were 3.28 and 3.63 in the Huaxian catchment (Fig. 5).

254 Figure 6 presents the results of the natural streamflow reconstruction using the  
 255 VIC and LSTM models. In the calibration period (1961–1980), the NSE values for  
 256 the Xianyang station were 0.67 (VIC) and 0.92 (LSTM). During the validation period  
 257 (1981–1990), the NSE values were 0.84 (VIC) and 0.92 (LSTM). For the Huaxian sta-  
 258 tion, the NSE values during the calibration period were 0.75 (VIC) and 0.97 (LSTM),  
 259 while in the validation period they were 0.89 (VIC) and 0.98 (LSTM). The overall simu-  
 260 lation results demonstrated a high level of accuracy.

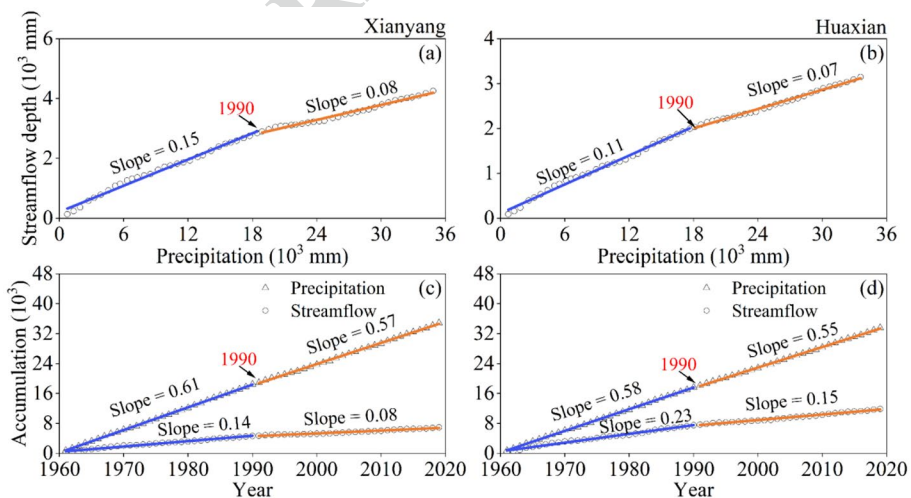


Fig. 4 The parameters of statistical analysis methods including DMC (a and b) and SCRAQ (c and d)

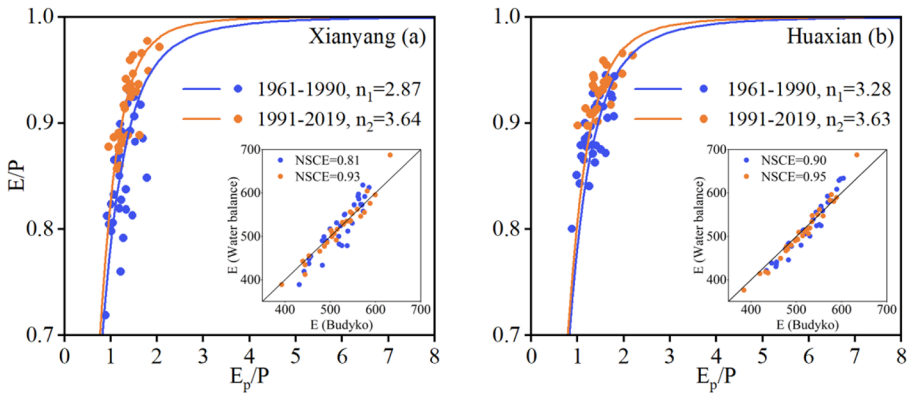


Fig. 5 Determine the catchment-specific parameter  $n$  of the Weihe River Basin

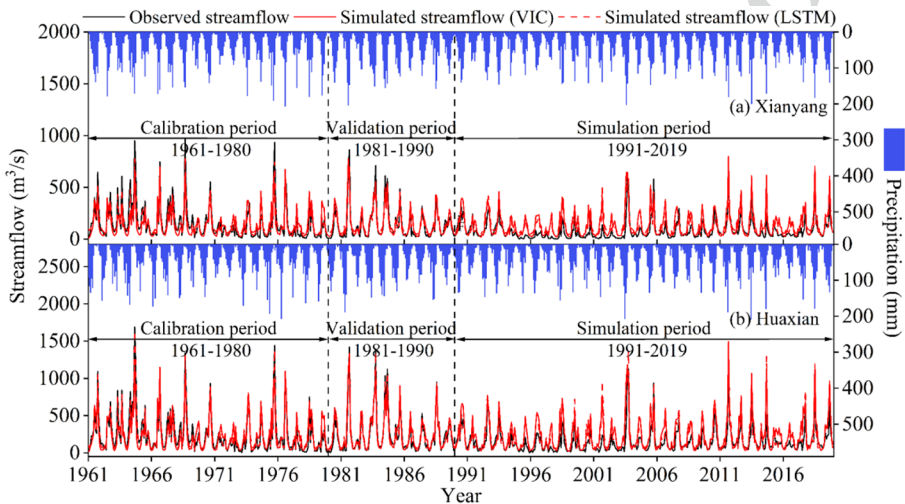


Fig. 6 Reconstruction of natural streamflow using hydrological model (VIC) and machine learning (LSTM) in the Weihe River Basin

261 **3.2.2 Relative Contribution**

262 Figure 7 provides a summary of the contributions of CC and HA to streamflow alteration  
 263 by traditional hydrological methods. In the Xianyang catchment, the contribution of CC  
 264 to streamflow alteration varied between 22.0% and 39.0% in period I, 10.8% and 41.0% in  
 265 period II, 5.1% and 40.6% in period III, and 14.0% and 40.1% in period IV. Additionally,  
 266 the average contributions of CC and HA to streamflow were 32.1% and 67.9% in period  
 267 I, 24.1% and 75.9% in period II, 18.4% and 81.6% in period III, and 26.0% and 74.0%  
 268 in period IV. Similarly, in the Huaxian catchment, the contribution of CC to streamflow  
 269 alteration ranged from 22.3% to 57.5% in period I, 15.5% to 38.7% in period II, 5.8% to  
 270 24.6% in period III, and 15.4% to 39.2% in period IV. The average contributions of CC and  
 271 HA to streamflow were 39.3% and 60.7% in period I, 25.8% and 74.2% in period II, 15.6%

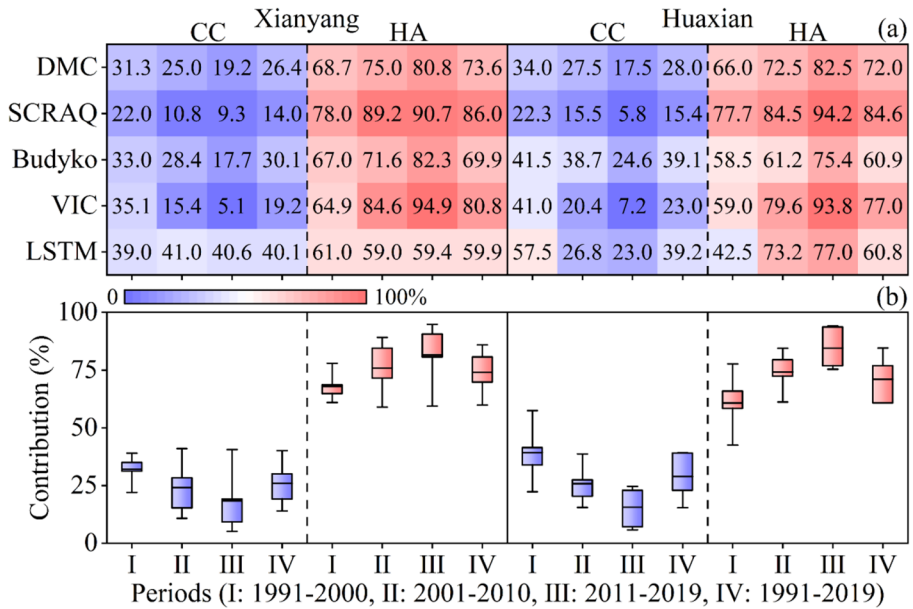


Fig. 7 Summary of the climatic and anthropogenic contributions to streamflow alteration based on traditional hydrological attribution methods in the Weihe River Basin

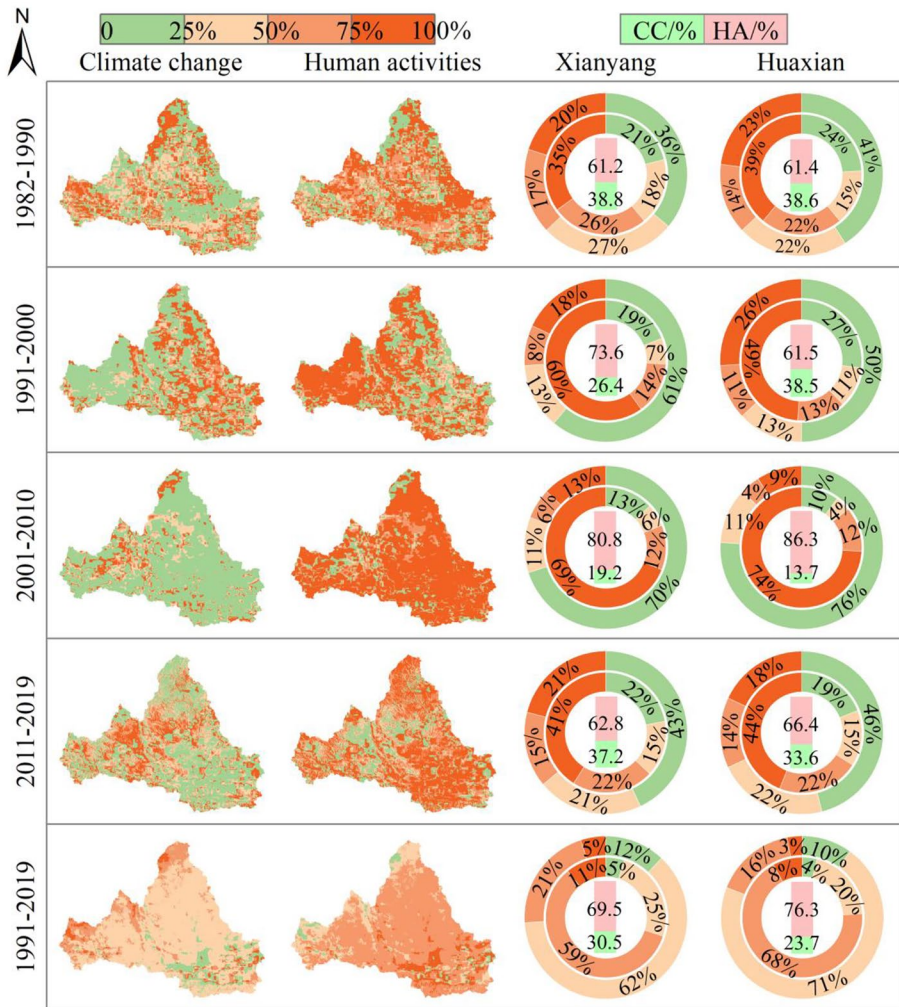
272 and 84.4% in period III, and 28.9% and 71.1% in period IV. Furthermore, the impact of CC  
 273 on streamflow alteration decreased from period I to period III.

274 **3.3 Relative Contribution Based on the RA Method**

275 Figure 8 illustrates the characterization of CC and HA contributions to NDVI alteration  
 276 using the RA method across multiple periods. During the baseline period, the CC and HA  
 277 contributions to NDVI variation in the Xianyang catchment were 38.8% and 61.2%, respec-  
 278 tively, while in the Huaxian catchment, which were 38.6% and 61.4% respectively. In the  
 279 variation period (IV), the CC and HA contributions to NDVI variation in the Xianyang  
 280 catchment were 30.5% and 69.5% respectively, whereas in the Huaxian catchment, which  
 281 were 23.7% and 76.3% respectively. Compared to the baseline period, the HA contributions  
 282 were significantly amplified during the variation period. Regions where HA accounted for  
 283 75% to 100% of NDVI alteration constituted 69% and 74% of the Xianyang and Huaxian  
 284 catchments respectively, representing the highest proportions. The contribution of HA to  
 285 NDVI alteration in the Xianyang and Huaxian catchments from 2001 to 2010 was 80.8%  
 286 and 86.3% respectively, primarily attributed to the implementation of the Grain to Green  
 287 Program in 1999 (Luan et al. 2021).

288 **3.4 Relative Contribution Coupled Climate, Vegetation and WW**

289 In the Xianyang catchment, compared to the baseline period, the contributions of MF, Lcc,  
 290 Lha, and WW to streamflow reduction during the variation periods were 26.0%, 13.5%,  
 291 30.9%, and 29.6%, respectively. in the Huaxian catchment, compared to the baseline

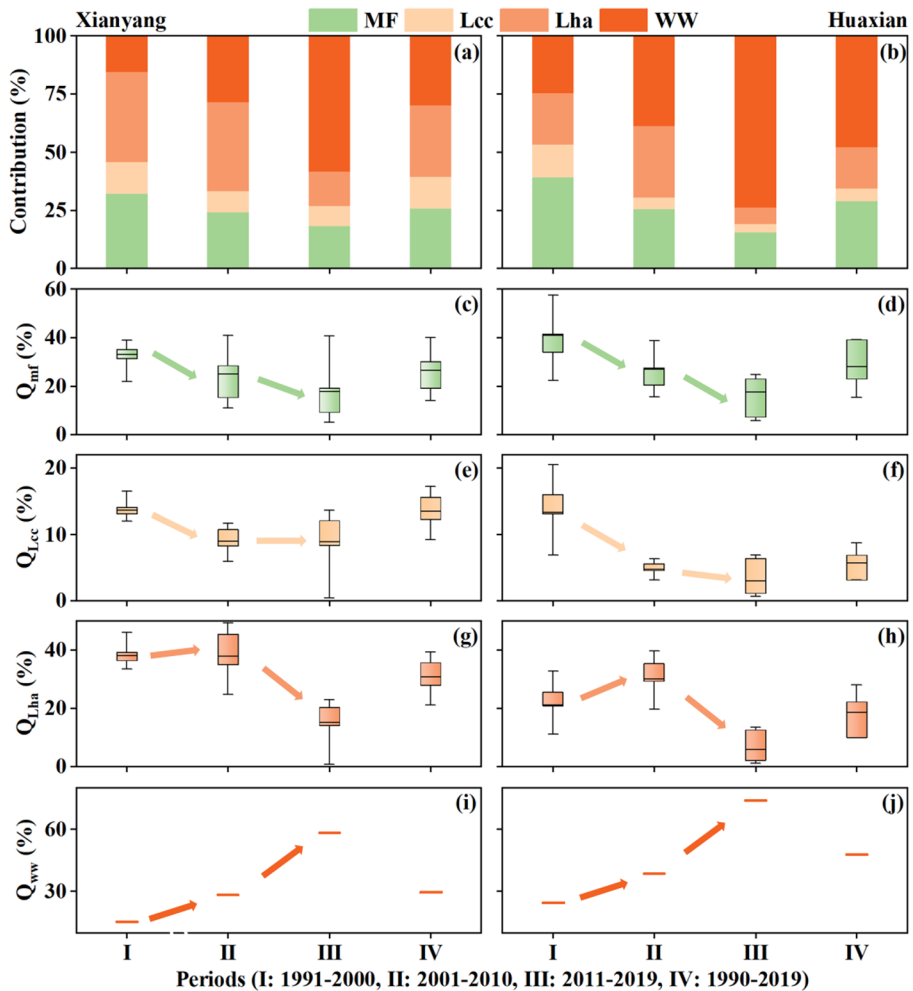


**Fig. 8** Quantifying climatic and anthropogenic contributions to NDVI alteration using residual analysis (RA) method over multiple periods in the Weihe River Basin. (The outer and inner circle represents the contributions of the proportion of climatic regions and HA regions and the histogram represents the climatic and anthropogenic contributions to NDVI alteration)

292 period, the contributions of MF, Lcc, Lha, and WW to streamflow reduction during the  
 293 variation periods were 28.9%, 5.5%, 17.7%, and 47.9%, respectively (Fig. 9a, b). These  
 294 findings indicate that the impact of WW on streamflow reduction is more significant in the  
 295 Huaxian catchment compared to the Xianyang catchment. This is primarily due to the con-  
 296 centration of population and agricultural areas in the lower reaches of the Huaxian catch-  
 297 ment (Yan et al. 2022).

298 Additionally, the average contributions of MF, Lcc, Lha, and WW to streamflow reduc-  
 299 tion varied across different periods within the variation period (Fig. 9c-j). Specifically, in  
 300 the Xianyang catchment, the contribution of MF to streamflow reduction decreased from

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**Fig. 9** Relative contribution coupled climate, vegetation and water withdrawal in the Weihe River Basin. The **a-b**: contribution of meteorological factors (MF), vegetation alteration due to climate change (Lcc), vegetation alteration due to human activities (Lha), and water withdrawal (WW) to streamflow reduction (average of three schemes). The **c-d, e-f, g-h, and i-j** are the variation in contributions of MF, Lcc, Lha, and WW to streamflow reduction in different periods

301 32.1% in period I to 18.4% in period III. The contribution of Lcc to streamflow reduction  
 302 decreased from 13.9% in period I to 8.7% in period III. The contribution of Lha to stream-  
 303 flow reduction decreased from 38.7% in period I to 14.6% in period III. The contribution  
 304 of WW to streamflow reduction increased from 15.4% in period I to 58.3% in period III.  
 305 In the Huaxian catchment, the contribution of MF to streamflow reduction decreased from  
 306 39.3% in period I to 15.6% in period III. The contribution of Lcc to streamflow reduction  
 307 decreased from 14.0% in period I to 3.6% in period III. The contribution of Lha to stream-  
 308 flow reduction decreased from 22.3% in period I to 7.0% in period III. The contribution  
 309 of WW to streamflow reduction increased from 24.5% in period I to 73.8% in period III.



310 There was a significant increase in Lha from period I to period II in the WRB, indicating  
311 that the vegetation greening resulting from the Grain for Green Program played a positive  
312 role in streamflow reduction (Luan et al. 2021). Moreover, the decrease in Lha from period  
313 II to period III in the WRB was primarily caused by a noticeable increase in WW.

## 314 4 Discussion

315 The traditional streamflow attribution methods are widely used for quantifying CC and  
316 HA contributions to streamflow alteration (Swain et al. 2021). However, these traditional  
317 approaches tend to underestimate the effects of CC and are unable to isolate the individual  
318 impacts of multiple HAs on streamflow (Li et al. 2022). In this study, a streamflow attribu-  
319 tion framework that serves as an effective tool for evaluating the impacts of MF, Lcc, Lha,  
320 and WW on streamflow alterations was proposed. On one hand, in comparison to previous  
321 findings regarding the impact of CC on streamflow (Fan et al. 2017), our research cor-  
322 rectes the underestimated influence of CC and quantifies the impact of vegetation and WW  
323 changes on streamflow. On the other hand, distinct from the Budyko and reduction runoff  
324 methods employed to differentiate the effects of land cover and WW on streamflow, our  
325 study utilizes the ratio of CC and HA to vegetation change in order to quantify the impacts  
326 of CC and HA on streamflow through land cover. This simplification of the method ena-  
327 bles a more straightforward distinction between the influences of land cover and WW on  
328 streamflow (Li et al. 2022).

329 Catchment hydrological processes involve intricate interactions among climate, vegeta-  
330 tion, and WW (Luo et al. 2020). In recent years, these factors have exhibited heightened  
331 temporal variability in response to a changing environment (Ahmed et al. 2022; Gholami  
332 et al. 2023). Consequently, the challenge lies in effectively disentangling the impacts of  
333 vegetation and WW changes on streamflow (Melo et al. 2023). In this study, firstly, we  
334 separate the impacts of MF on streamflow, followed by the separation of the effects of  
335 WW on streamflow utilizing global WW data. The remaining impacts are then attributed  
336 to land cover change. The contribution of CC and HA to streamflow through land cover  
337 is substituted by the proportion of CC and HA on vegetation change. Our findings reveal  
338 that the HA-induced greening of vegetation in the WRB during period III had a signifi-  
339 cant influence on streamflow generation (Fig. 9g, h). Moreover, the impact of vegetation  
340 on streamflow was found to be less pronounced compared to the effects of CC and direct  
341 HA (Fig. 9). These research conclusions are consistent with the findings of Jin and Duan  
342 (2019). The methodology developed in this study provides a solution for quantifying the  
343 indirect effects of CC on streamflow via vegetation, serving as a relatively simple scientific  
344 tool for attributing streamflow alterations resulting from climate, vegetation, and WW.

345 Finally, it is important to acknowledge certain limitations of the streamflow attribution  
346 framework proposed in this study. Specifically, the framework only takes into account two  
347 human activities, vegetation and WW. When applying the streamflow attribution frame-  
348 work to other regions, additional factors such as damming and irrigation should be consid-  
349 ered (Swain et al. 2021; Wang et al. 2022). Future research endeavors could aim to develop  
350 schemes that optimize the attribution of streamflow alterations caused by land cover,  
351 and subsequently integrate them into the streamflow attribution framework. This would  
352 enhance the robustness and applicability of the framework in capturing a more comprehen-  
353 sive understanding of the complex interactions between human activities and streamflow.

## 354 5 Conclusions

355 In this study, a complementary streamflow attribution framework coupled climate, vegeta-  
356 tion and WW was proposed. Compared with streamflow attribution methods, our approach  
357 accounts for the impacts of both vegetation and WW changes on streamflow. When com-  
358 pared to similar approaches, we streamline the simulation of WW by utilizing global WW  
359 data, allowing us to quantify the effects of CC and HA on streamflow through land cover.  
360 The WRB in Northwest China was selected as the case study area to perform the proposed  
361 framework. The results demonstrate that, in comparison to the baseline period, the aver-  
362 age contributions of MF, Lcc, Lha, and WW to streamflow reduction during the variation  
363 periods were 28.9%, 5.5%, 17.7%, and 47.9% respectively in the WRB. This methodology  
364 provides a relatively straightforward scientific tool for attributing streamflow alterations  
365 resulting from MF, Lcc, Lha, and WW in various real-world case studies. Furthermore, the  
366 impact of WW on streamflow can be further subdivided based on the proportion of water  
367 used for industrial, agricultural, and domestic. However, vegetation change alone cannot  
368 fully replace the consideration of land cover in streamflow attribution. Future research  
369 efforts may focus on developing schemes that optimize the attribution of streamflow altera-  
370 tions caused by land cover, which can then be incorporated into the streamflow attribution  
371 framework.

372

373 **Author Contribution** Conceptualization: Shanhu Jiang; Yongwei Zhu; Methodology: Denghua Yan; Hao  
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379 **Data Availability** Data will be made available on request.

## 380 Declarations

381 **Ethical Approval** Not applicable.

382 **Consent to Participate** Not applicable.

383 **Consent to Publication** Not applicable.

384 **Competing Interests** The authors declare that they have no competing interests.

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