



1 **Spatiotemporal variations of carbon-water-hydraulic risk for *Pinus tabuliformis***

2 **L. Plantations on the Loess Plateau under Future Climate Change**

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19 **Abstract.** As a native perennial tree, *Pinus tabuliformis* L. (PT) has been widely
20 planted on the Chinese Loess Plateau for ecological restoration. However, climate
21 change impacts on water resources will poses a new challenge for sustainability of
22 restored ecosystems. To clarify the plantations carbon sequestration and water
23 consumption, as well as their underlying physiological mechanisms, this study coupled
24 the integrated BBGC-Sperry model with CMIP6 meteorological data under SSP126,
25 SSP245, and SSP585. Daily transpiration, soil water content, and leaf water potential,
26 along with multi-site total growing-season transpiration and aboveground biomass data,
27 were used to validate the BBGC-Sperry model. The validated model simulated the
28 dynamics of NPP, actual evapotranspiration (ET) and annual average percentage loss
29 of whole-plant hydraulic conductivity (APLK) for PT plantations at 130 meteorological
30 stations on the Loess Plateau. We integrated a “carbon-water-hydraulic risk index”
31 (CWHRI) based on NPP, ET, and drought-induced mortality risk probability (DMRP)
32 to assess ecosystem sustainability. These simulations covered the baseline period
33 (2000-2024) and three future periods (2025-2049, NFP; 2050-2074, MFP; and 2075-
34 2099, FFP). The results indicate that the mean NPP will decrease by 4%-27% except in
35 the FFP under the SSP585 while the mean ET and APLK will increase by 0.05%-61%
36 and 13%-84%, respectively. The CWHRI will decline by 23%-44%, driven directly by
37 NPP and indirectly by water-related environmental factors. The spatial dynamics of
38 CWHRI will decline from southeast to northwest. These findings indicate the rising
39 DMRP of PT plantations will threaten the sustainability of restored ecosystems on the
40 Loess Plateau in the future.

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42 **Keywords:** Climate change; BBGC-Sperry model; Net primary productivity; Actual

43 evapotranspiration; Drought-induced mortality risk; The Loess Plateau



44 **1 Introduction**

45 Plantations play a vital role in ecological restoration (Fan et al., 2024; Chen et al., 2025)
46 and significantly contributes to global biogeochemical cycles (Piao et al., 2020).The
47 monoculture plantations can quickly boost regional ecosystem productivity and carbon
48 storage (Li Q. et al., 2025). However, against the backdrop of rising global temperatures
49 and shifting precipitation patterns, the frequent occurrence of compound drought events
50 poses an increasingly severe threat to the physiological processes of forest plantations,
51 while triggering a series of negative hydrological feedback effects, especially in
52 ecologically fragile regions (Tang and Chen, 2025; Qi et al., 2025; Zhou et al., 2019;
53 Feng et al., 2016; Brodribb et al., 2020; Ma et al., 2023; Liu et al., 2023; Li Z. et al.,
54 2025). These phenomena have raised concerns about the production, ecological benefits,
55 and drought-induced mortality risk of plantations under the future climate change (Li
56 Q. et al., 2025). Therefore, accurately assessing the response of plantation productivity,
57 evapotranspiration, and drought-induced mortality risk to climate change is a critical
58 prerequisite for developing adaptive management strategies and ensuring ecological
59 security.

60 Most current regional-scale studies rely on environmental surrogate indicators such
61 as meteorological drought indices, soil moisture, forest net primary productivity (NPP),
62 or remote sensing-based vegetation greenness or productivity models to obtain
63 information on ecosystem or individual plant growth (Jiao et al., 2021; Li et al., 2021;
64 Chen Z. et al., 2024; He et al., 2024; Wang et al., 2025). These traditional assessment
65 methods can characterize ecological functionality macroscopically, but they fail to



66 capture the critical internal physiological mechanisms underlying tree survival under
67 drought stress, resulting in a gap in understanding of drought-induced mechanisms in
68 forests under climate change. These methodological limitations may lead to
69 overestimate vegetation growth, as plant physiological responses occur faster than
70 canopy changes under drought stress (Tang et al., 2026). Therefore, accurately
71 assessing drought-induced mortality risk at the regional scale can provide a deeper
72 understanding of the security and sustainability of plantation restoration ecosystems.

73 Currently, investigating the mechanisms of drought-induced tree mortality is
74 daunting due to the complex physiological and ecological processes involved
75 (McDowell et al., 2008, 2022; Arend et al., 2021). A comprehensive drought response
76 mechanism should start from climatic drivers, proceed through the regulation of
77 ecosystem hydrological processes, and ultimately affect the physiological processes of
78 individual trees, thereby determining their mortality probability (McDowell et al., 2022;
79 Ma et al., 2023). At the regional scale, field monitoring is time-consuming and labor-
80 intensive. Therefore, there is an urgent need for models that integrate plant hydraulic
81 and ecological processes. Zhang et al. (2020) developed the eco-hydrological-hydraulic
82 (BBGC-Sperry model) model by coupling a plant hydraulic process model (Sperry
83 model) with a biogeochemical model (Biome-BGC model). This model uses a supply -
84 demand function to overcome the limitations of empirical functions in describing plant
85 water use responses to soil and atmospheric drought. Yan et al.(2022) have successfully
86 used this model to assess the drought-induced mortality risk of *Robinia pseudoacacia*
87 plantations at four meteorological stations across a typical precipitation gradient on the



88 Loess Plateau. [Wu et al. \(2026\)](#) improved the Penman-Monteith equation, which used
89 in the BBGC-Sperry model for evapotranspiration calculations, enhancing its ability to
90 account for the effects of elevated atmospheric CO₂ on evapotranspiration. This
91 improvement enabled accurate assessment of actual evapotranspiration (ET) in PT
92 plantations on the Loess Plateau. These model improvements and applications provide
93 a solid foundation for assessing the growth dynamics of plantations on the Loess
94 Plateau. However, existing studies have been largely conducted at the site scale, and
95 the application of this model at the regional scale remains to be validated. The improved
96 BBGC-SPERRY model allows for more accurate simulations of key vegetation growth
97 and physiological indicators, including net primary productivity (NPP),
98 evapotranspiration (ET), and the annual average percentage loss of whole-plant
99 hydraulic conductance (APLK). It serves as a reliable tool for revealing the true
100 vulnerability of forests, avoiding systemic misjudgments, and supporting the
101 construction of a “Carbon-Water-Hydraulic Risk Index” (CWHRI) framework.

102 The Loess Plateau of China is one of the most climate-sensitive regions globally,
103 with a warming rate above the global average and increasing variability in precipitation
104 ([Yan et al., 2022](#)). To address land degradation and wind erosion, large-scale
105 afforestation projects, such as the "Grain-for-Green" program, have been implemented
106 in the region since the 1990s ([Li et al., 2021](#)). *Pinus tabuliformis* L. (PT) plantations
107 have been widely planted due to their strong drought tolerance and soil fixation capacity,
108 and now form an important regional ecological barrier ([Chen et al., 2008](#)). However,
109 PT plantations may lead to a continuous decline in soil water storage due to their high



110 water consumption, potentially resulting in the formation of stable dry layers (Chen S.
111 et al., 2024). This suggests a potential risk of water imbalance, making tree growth
112 increasingly dependent on unstable precipitation inputs. In some restored areas, PT
113 plantations have already exhibited browning. The uncertainty of future global
114 precipitation patterns is expected to further increase the sensitivity of forest ecosystems
115 to interannual precipitation fluctuations, potentially leading to growth decline, crown
116 dieback, and even tree mortality (Liu et al., 2020). Although the abovementioned risks
117 have received some attention, systematic, mechanistic long-term predictions of the
118 growth dynamics, physiological stress, and spatial variability patterns of PT plantations
119 under multiple future climate scenarios are still lacking.

120 Therefore, a single-site experiment was conducted in a typical ecological
121 restoration area in Ansai, Shaanxi during the 2024-2025 growing seasons (May 1-
122 September 30). The modified BBGC-Sperry model was validated using measured daily
123 transpiration (T_{day}), midday leaf water potential (Ψ_{md}), and soil water content (SWC),
124 as well as total growing-season transpiration and aboveground biomass data collected
125 from other meteorological stations within the study area. The validated model was used
126 to simulate the spatiotemporal variations of NPP, ET, and APLK at 130 meteorological
127 stations in the study area from 2000 to 2024, and to project future conditions the next
128 75 years under three Shared Socioeconomic Pathways (SSP126, SSP245, SSP585)
129 from CMIP6. The objectives of this study were to: 1) validate application of the
130 modified BBGC-Sperry model to PT plantations in the study area; 2) reveal
131 spatiotemporal variations of NPP, ET and APLK in PT plantations under climate



132 change; 3) develop a new index to assess the ecological functionality based on NPP, ET
133 and drought-induced mortality risk (DMRP) and analyze its spatiotemporal variations
134 and influencing factors . The results could provide insights into the adaptability of PT
135 plantations to future climate change and their potential hydrological and physiological
136 vulnerabilities on the Loess Plateau.

137

138 **2 Materials and methods**

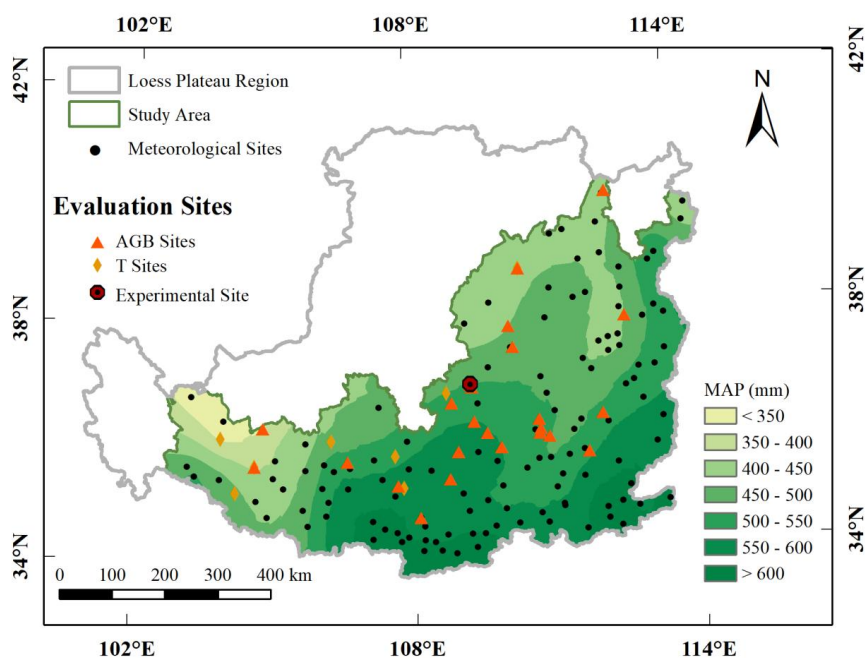
139 **2.1 Study area**

140 To control soil and water erosion, large-scale vegetation restoration projects (e.g., the
141 Grain-for-Green Program and the Three-North Shelter Forest Program) were
142 implemented by China's Central Government in this region in the late 1990s ([Jia et al.,](#)
143 [2017](#)). Native PT, a pioneer species for vegetation restoration, was widely planted due
144 to its drought resistance and is now mainly distributed across Gansu, Shaanxi, and
145 Shanxi provinces on the Loess Plateau ([Wang, 2016](#)). Therefore, the green area in [Fig.](#)
146 [1](#) was selected as the simulation area to analyze the growth and drought-induced
147 mortality risk of PT plantations. The study area (102.68-114.55°E, 33.72-40.74°N) is
148 located in the Loess Plateau, covering approximately 380,000 km² ([Fig. 1](#)), and
149 encompasses diverse topographic features with hills, gullies, ridges, and basins. The
150 predominant soil types include silt-clay, silt-clay-loam, silt-loam, loam, and sand-loam
151 ([Jia et al., 2019](#)). From southeast to northwest, the climate transitions from semi-humid
152 to semi-arid, the mean annual precipitation (MAP) decreases from 700 to 200 mm with
153 55-78% occurring from June to September, and the mean annual temperature (MAT)



154 ranges from 14.3 to 3.6 °C (Zhang et al., 2024b). The region is characterized by loess
155 deposits ranging from 30 to 200 m thick. Precipitation in the study area is the primary
156 source of recharge and the depth to groundwater is typically between 30 and 100 m
157 (Zhu et al., 2018).

158



159

160 **Figure. 1** Map depicting the location of the study area on the Loess Plateau showing
161 the distribution of the 130 modeling sites, nine sites where growing season transpiration
162 (T) data were collected, 27 sites where aboveground biomass (AGB) data were
163 collected, and one experimental site (Ansai).

164

165 2.2 BBGC-Sperry model description

166 BBGC-Sperry is a coupled model integrating the biome biogeochemical cycle model



167 (Biome-BGC model) with the plant supply-demand hydraulic model (Sperry model).
168 Conventional climate data, soil parameters, and physiological-ecological parameters
169 were incorporated into this model to simulate the dynamic changes in plant hydraulic
170 properties at the daily scale, along with water, carbon, nitrogen, and nitrogen cycling
171 processes. The BBGC-Sperry model is described in detail in previous articles ([Zhang
172 et al., 2020](#); [Yan et al., 2022](#)). Here, we briefly outline several key processes.

173 **2.2.1 Water cycle**

174 The only water input to the system occurs through precipitation (rain or snow). The
175 amount of intercepted precipitation depends on the canopy interception coefficient and
176 the leaf area index (LAI). In this model, snowfall reaches the soil surface directly
177 without being intercepted by the vegetation canopy and its sublimation and melt are
178 estimated based on daily air temperature and net solar radiation. Water outflow includes
179 soil evaporation and canopy transpiration (canopy evaporation and evaporation from
180 intercepted water), which are calculated based on modified Penman-Monteith functions
181 with different conductivity types. The modified Penman-Monteith equation takes into
182 account the effect of atmospheric carbon dioxide concentrations on overall surface
183 resistance ([Wu et al., 2026](#)). Water transport processes in the soil-plant-atmosphere
184 (SPAC) system were simulated by the Sperry model. The detailed modification of the
185 Sperry model can be found in [Zhang et al. \(2020\)](#). The Sperry model divides the SPAC
186 into serial components of leaves, stems, roots, and rhizosphere. Supply and demand
187 functions are employed to calculate water flux, whole-plant hydraulic conductance
188 (k_{plant}), and the distribution of water potential and hydraulic conductance within the



189 SPAC system. The vulnerability curves for each component describe the attenuation of
190 hydraulic conductance as water potential decreases, with steady-state flow calculated
191 by integral transformation. The root system is stratified by root density, employing a
192 multidimensional Newton-Raphson iteration method to solve for water potential and
193 water uptake rates within each root layer. Soil moisture movement is simulated using a
194 hydrological submodel based on the Richards equation (Huang et al., 2013).

195 **2.2.2 Carbon and nitrogen cycle**

196 The only addition of C to the system is through photosynthesis. C is removed from
197 the system during all autotrophic (maintenance and growth) processes, heterotrophic
198 (decomposition) processes, and fire or harvest disturbance events. The addition of N to
199 the system is divided into plant N pools and soil N pools. Plant N enters the system
200 through leaf litter, while soil mineralized N is released by the slowest-releasing organic
201 matter, N dry and wet deposition from the atmosphere, and N fixation. Mineralized N
202 is lost from the system by leaching and volatilization. The model uses a two-leaf
203 representation of the canopy to model all canopy photosynthesis, which is based on the
204 enzymatic kinetics of Rubisco in relation to temperature, availability of CO₂, and rate
205 of Rubisco regeneration (Farquhar et al., 1980). For autotrophic respiration, respiration
206 maintenance is modeled using the Q₁₀ function of temperature and nitrogen content.
207 Heterotrophic respiration is assumed to be a constant proportion of all new tissue
208 growth (Yan et al., 2022).

209 **2.3 Model evaluation**

210 **2.3.1 Hydrological process validation**



211 Daily transpiration (T_{day}), SWC, and midday leaf water potential (Ψ_{md}) during the
212 growing season in PT plantations were used to evaluate the hydrological process of the
213 BBGC-Sperry model. Thus, we established an experimental PT plantation site in Ansai
214 District, Shaanxi Province on May 1, 2024. This area is a key zone for soil and water
215 conservation projects. Field observations were conducted during the 2024 and 2025
216 growing seasons (1 May to 30 September). The experimental plot had an area of 20 m
217 \times 20 m and a tree density of 1600 stems ha^{-1} . Additionally, we measured the sapwood
218 thickness and diameter at breast height of 20 trees near the experimental area using
219 growth cones and vernier calipers and established a regression equation ($R^2=0.99$)
220 linking diameter at breast height (D) to sapwood area (A_s) in the PT plantation, as
221 follows:

$$222 \quad A_s = 0.34D^{2.095} \quad (1)$$

223 Stem sap flow sensors were used to measure the sapwood flux density. First, we
224 selected eight representative sample trees based on the distribution of breast height
225 diameter classes. Stem sap flow sensors (Granier type, probe length 10 mm, diameter
226 1.2 mm, with a 40 mm spacing between the heated probe and reference probe) were
227 uniformly installed at the breast height diameter (1.3 m) to monitor the dynamic
228 changes in sap flow density during the growing season in the PT plantations. During
229 installation, sufficient exposure of the phloem at breast height was ensured. To
230 minimize rainfall and solar radiation effects, sensors were mounted on the shaded side
231 of the trunk. Additionally, the gap between the two probes and the trunk was sealed
232 with petroleum jelly and wrapped in multiple layers of radiation-shielding aluminum



233 foil. The sensor was connected to a CR1000 datalogger (Campbell Scientific, Logan,
234 UT, USA) and an AM16/32 data expansion board (Campbell Scientific, USA), scanning
235 and collecting data every 30 s while recording hourly averages. The CR1000 datalogger
236 was powered by a 12-volt DC battery and an ES-VR2 voltage regulator, supplemented
237 by solar panels. Based on the measured dual-probe temperature difference from the
238 trunk sap flow sensor, the sapwood flux density (F_d ; $\text{g cm}^{-2} \text{ s}^{-1}$) was calculated using
239 Granier's (1987) empirical equations (2) as follows:

$$240 \quad F_d = \alpha K^\beta \quad (2)$$

241 where α and β are fitting parameters determined by the calibration curve and estimated
242 at 0.013 and 1.024, respectively (Song et al., 2023). K is the dimensionless fluid flow
243 index, which is calculated using the following equation:

$$244 \quad K = \frac{(\Delta T_{\text{max}} - \Delta T)}{\Delta T} \quad (3)$$

245 where ΔT is the temperature difference ($^{\circ}\text{C}$) between two probes at any given time and
246 ΔT_{max} is the maximum value of ΔT ($^{\circ}\text{C}$). The average sap flow density (J_s ; $\text{g m}^{-2} \text{ s}^{-1}$)
247 in the tree's sapwood was calculated using the following equation:

$$248 \quad J_s = \frac{\sum_{i=1}^5 F_{di} \times A_{si}}{\sum_{i=1}^5 A_{si}} \quad (4)$$

249 where i is the i^{th} sample tree, and F_{di} and A_{si} represent the sapwood sap flow density and
250 sapwood area of the i^{th} sample tree, respectively. The canopy transpiration rate (T_{day} ;
251 mm s^{-1}) was calculated using :

$$252 \quad T_{\text{day}} = J_s \times \frac{A_{\text{st}}}{A_{\text{g}}} \quad (5)$$

253 where A_{st} and A_{g} are the total sapwood area of trees in the plot (m^2), and J_s is defined



254 as in Eq. 4.

255 This study also collected observational data on the transpiration (T) during the
 256 growing season in the study area's PT plantations. A total of 48 T values were measured,
 257 covering nine meteorological stations, using two methods: (1) stem sap flow was
 258 measured using the heat probe method and converted to T_{ra} ; and (2) T was calculated
 259 using the water balance equation based on growing season precipitation (Pr, mm),
 260 runoff (R, mm), soil evaporation (E, mm), and the change in soil water storage (ΔS ,
 261 mm) during the growing season: $T = Pr - R - E + \Delta S$.

262 Soil moisture sensors (EC-5, Decagon, USA) connected to a CR1000 datalogger
 263 were used to monitor the SWC at 20, 40, 60, 80, 100, 160, 200, 300, and 500 cm below
 264 the soil surface. The sensors exhibited a measurement accuracy of $\pm 3\%$. To calibrate
 265 the sensors, SWC was also measured monthly using an oven-drying method. The
 266 established calibration equations are shown in Table 1.

267

268 **Table 1** Calibration equations for EC-5 soil moisture sensors in the *Pinus tabuliformis*

269 L. plantations at the Ansai site.

Soil depth (cm)	calibration equation	R ²
0-20	$y=0.5693x+1.7374$	0.93
20-40	$y=0.7054x+2.3079$	0.91
40-60	$y=0.7236x+3.2223$	0.99
60-80	$y=0.9646x+2.8214$	0.93
80-100	$y=1.0065x+5.7863$	0.95
100-140	$y=1.4498x+2.2259$	0.93
140-160	$y=1.5845x-0.0117$	0.92
160-200	$y=1.0123x+4.7166$	0.88
200-300	$y=0.664x+3.2464$	0.93
300-500	$y=0.5928x+2.7618$	0.87

270



271 Ψ_{md} was measured between 12:00 PM and 2:00 PM each month during the growing
 272 season using a portable plant water potential meter (PMS Instrument Co., Corvallis,
 273 OR, USA). For each measurement, a branch exposed to sunlight was cut from the
 274 upper-middle canopy using pruning shears. Pine needle samples were collected from
 275 the harvested branch using a small knife, and a bundle of pine needles immediately
 276 wrapped tightly with raw tape. Samples were then put in the pressure chamber for
 277 measurement. Simultaneously, an electronic magnifying glass was used to observe the
 278 condition of the petiole cut surface. When small water droplets appeared on the petiole
 279 cut surface, the inflation valve was quickly closed and the numbers on the pressure
 280 gauge interface recorded, which represented the instantaneous Ψ_{md} . Each treatment
 281 included six replicates.

282 2.3.2 Growth process validation

283 To evaluate the growth process of the BBGC-Sperry model, this study collected
 284 observational data on aboveground biomass (AGB) during the growing season in the
 285 study area's PT plantations. AGB is highly correlated with indicators such as NPP and
 286 LAI. Therefore, AGB can be considered a representative indicator that is readily
 287 available. A total of 74 AGB values were obtained using the allometric growth equation
 288 (Table 2), covering 27 meteorological stations.

289

290 **Table 2** Biomass equations for *Pinus tabuliformis* L. (Zhou et al., 2018)

Organs	Biomass equations	R ²
Stems	$W=0.0485 \times (D^2H)^{0.8510}$	0.99
Branches	$W=0.0245 \times (D^2H)^{0.7991}$	0.99
Leaves	$W=0.0500 \times (D^2H)^{0.6308}$	0.98



$$\frac{\text{Roots}}{W=0.0298 \times (D^2 H)^{0.7866}} \quad 0.99$$

291 Notes: W represents biomass (kg C m^{-2}); D is diameter at breast height (cm); H is tree
292 height (m).

293

294 **2.4 Data sources**

295 **2.4.1 Meteorological datasets**

296 Meteorological data for 130 simulated sites from 2000 to 2024 were obtained from the
297 China National Meteorological Center (<http://data.cma.cn/>), including daily maximum
298 temperature, minimum temperature, relative humidity, and precipitation, among other
299 meteorological data. Future meteorological data were obtained from NASA's Earth
300 Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6)
301 (<https://doi.org/10.7917/OFSG3345>) (Thrasher et al., 2022). This dataset features a
302 resolution of 0.25° . We selected daily datasets for six models (CanESM5, FGOALS-g3,
303 GFDL-CM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, and MRI-ESM2-0) under three
304 scenarios (SSP126, SSP245, and SSP585). The CO_2 emissions under the three scenarios
305 are shown in Fig. S1 (Melnikova et al., 2023). The datasets include daily maximum
306 temperatures, daily minimum temperatures, and precipitation data for the period 2025–
307 2099 for the same 130 meteorological stations.

308 Based on the phased characteristics of carbon dioxide emission trajectories under
309 different Shared Socioeconomic Pathways (SSP) scenarios, and considering the period
310 around 2050 marks a critical turning point for multiple emission scenarios, both SSP126
311 and SSP245 exhibit a trend of flat or slowly declining emissions after 2075. To more
312 accurately depict dynamic changes in various variables, this study divided the future



313 time period into three phases: near-future period (NFP; 2025-2049), mid-future period
314 (MFP; 2050-2074), and far-future period (FFP; 2075-2099). The Mountain Climate
315 Simulator (MT-CLIM) program ([https://www.umt.edu/numerical-terradynamic-](https://www.umt.edu/numerical-terradynamic-simulation-group/project/mt-clim.php)
316 [simulation-group/project/mt-clim.php](https://www.umt.edu/numerical-terradynamic-simulation-group/project/mt-clim.php)) (Thornton et al., 2002) was used to calculate
317 solar radiation, daylight average partial pressure of water vapor, and day length based
318 on acquired meteorological data.

319 **2.4.2 Soil hydraulic properties**

320 The soil parameters required for this study included saturated soil moisture content (θ_s),
321 residual soil moisture content (θ_r), soil parameters (α and n), and saturated hydraulic
322 conductivity (K_s). At the Ansai experimental site, we measured K_s and soil moisture
323 characteristic curves using the ring knife method in the laboratory. We derived the VG
324 model using RETC software to determine other soil hydraulic parameters (van
325 [Genuchten, 1980](#)). Clay, silt, sand, and bulk density data for the 130 simulated sites
326 were obtained from the SoilGrid250m dataset (<https://www.soilgrids.org/>). Soil K_s was
327 sourced from the Northwest Arid Region Soil Hydraulic Parameters dataset ([Zhang et](#)
328 [al., 2024a](#)). Soil moisture characteristic curves were obtained using the Arya-Paris
329 model ([Arya et al., 1999](#)), and the VG model was also derived using RETC software to
330 determine θ_s , θ_r , α , and n .

331 **2.4.3 Eco-physiological parameters**

332 The ecological and physiological parameters and values used in this simulation are
333 shown in [Table S1](#), along with those for PT plantations in the Biome-BGC model from
334 previous studies. Xylem vulnerability curves (VCs) for PT were determined using the



335 benchtop dehydration method (Sperry et al., 1988) (Fig. S2). We assumed VC
336 parameters were the same for roots, stems, and leaves. The maximum whole-plant
337 hydraulic conductance per leaf area, maximum diffusive conductance, and average
338 proportion of rhizosphere resistance were determined based on transpiration rates
339 observed at the Ansai site in 2024 (Sperry et al., 2016; Tai et al., 2018; Wolfe et al.,
340 2016).

341 **2.5 Assessment of drought-induced mortality risk**

342 Under drought stress, plants regulate stomatal function to influence carbon metabolism
343 processes, which is considered a core mechanism in drought-induced mortality. A
344 prolonged high daily percentage loss of whole-plant hydraulic conductance (PLK)
345 serves as a key indicator of drought mortality risk, calculated as follows:

$$346 \quad \text{PLK} = \left(1 - \frac{k_{\text{plant}}}{k_{\text{max}}} \right) \times 100\% \quad (6)$$

347 where k_{plant} is the whole plant hydraulic conductance and k_{max} is the maximum soil-
348 plant hydraulic conductance. Annual average PLK (APLK, %) reflects an inter-annual
349 variation in plant hydraulic security. We assumed the xylem embolism of PT could not
350 be recovered during the growing season. New plant tissue growth the next spring results
351 from the generation of root and stem pressure (Choat et al., 2018). An APLK value of
352 60% is widely accepted to represent the threshold at which trees face a high risk of
353 mortality (McDowell et al., 2013). Therefore, we also used this value to assess the
354 drought-induced mortality risk. Furthermore, we defined the probability value where
355 $\text{APLK} \geq 60\%$ as DMRP. The primary long-term objectives for the PT plantations in this
356 study area are soil and water conservation and ecosystem restoration. The functional



357 cycle for stand stability of PT plantations ranges from 20 to 50 years (Zhang et al.,
358 2024b). The study area is divided into high-risk (DMRP > 5%), medium-risk (2% ≤
359 DMRP ≤ 5%), and low-risk (DMRP < 2%) zones with drought mortality event
360 recurrence intervals of < 20, 20-50, and > 50 years, respectively.

361 **2.6 Calculation of carbon-water-hydraulic risk index**

362 To comprehensively assess the impact of future climate change on the sustainability of
363 PT plantations, this study developed a carbon-water-hydraulic risk index (CWHRI) by
364 integrating carbon assimilation, water consumption, and plant hydraulic risk into a
365 unified metric. These three components were selected because they represent key
366 dimensions of plantation functioning that are commonly evaluated separately.
367 Specifically, NPP reflects carbon sequestration and serves as the positive contribution
368 to sustainability, ET characterizes water consumption, and DMRP represents the
369 probability of tree mortality associated with drought-induced hydraulic stress. The
370 CWHRI is formulated as follows:

$$371 \quad \text{CWHRI} = \frac{\text{NPP}}{\text{ET}} \times (1 - \text{DMRP}) \quad (7)$$

372 where (1-DMRP) represents the survival probability under drought stress. The unit of
373 CWHRI is g C kg⁻¹ H₂O, representing the expected carbon gain per unit water
374 consumed after accounting for drought-induced mortality risk. The multiplicative form
375 ensures that as DMRP approaches 1 (certain mortality), CWHRI approaches zero
376 regardless of NPP or ET, reflecting the reality that a dying tree contributes nothing to
377 ecosystem function even if its short-term productivity appears normal. A higher value
378 of CWHRI indicates safer water transport in plantations and greater efficiency in using



379 water to support growth.

380 **2.7 Statistical analyses**

381 Annual mean NPP, ET, APLK, DMRP, and CWHRI were calculated for the baseline
382 period and NFP, MFP, and FFP under three future climate scenarios (SSP126, SSP245,
383 and SSP585). Spatial distribution maps were generated using Kriging interpolation in
384 ArcGIS 10.8 software. Annual values for the study area were obtained by weighting
385 annual data from 130 stations using the Thiessen polygons method. Temporal variations
386 of indicators were analyzed using one-way analysis of variance (ANOVA), with
387 multiple comparisons performed using Duncan's test at a significance level of $p < 0.05$.
388 A multiple linear regression method was used to calculate the contribution of NPP, ET,
389 and DMRP to changes in CWHRI. The importance of six meteorological variables
390 (mean annual precipitation, MAP; mean annual temperature, MAT; mean annual
391 maximum temperature, MAT_{max} ; mean annual minimum temperature, MAT_{min} ; mean
392 annual vapor pressure deficit, VPD, mean annual soil water storage, SWS) to dynamic
393 changes of CWHRI was assessed using XGBoost. Hyperparameters were tuned through
394 five-fold cross-validation combined with grid search, while early stopping was applied
395 to track validation error (Gong et al., 2026). The key variables identified by the
396 XGBoost model were considered as the driving factors behind dynamic changes in
397 CWHRI.

398 Model accuracy was evaluated using the coefficient of determination (R^2), mean
399 absolute error (MAE), root mean square error (RMSE), relative root mean square error
400 (rRMSE), and Nash-Sutcliffe efficiency coefficient (NSE) (Zhang et al., 2024b). The



401 NSE is used to measure the goodness of fit of a model, with values closer to 1.0
402 indicating higher simulation accuracy. Lower values of MAE, RMSE, and rRMSE
403 indicate higher accuracy.

404

405 **3 Results**

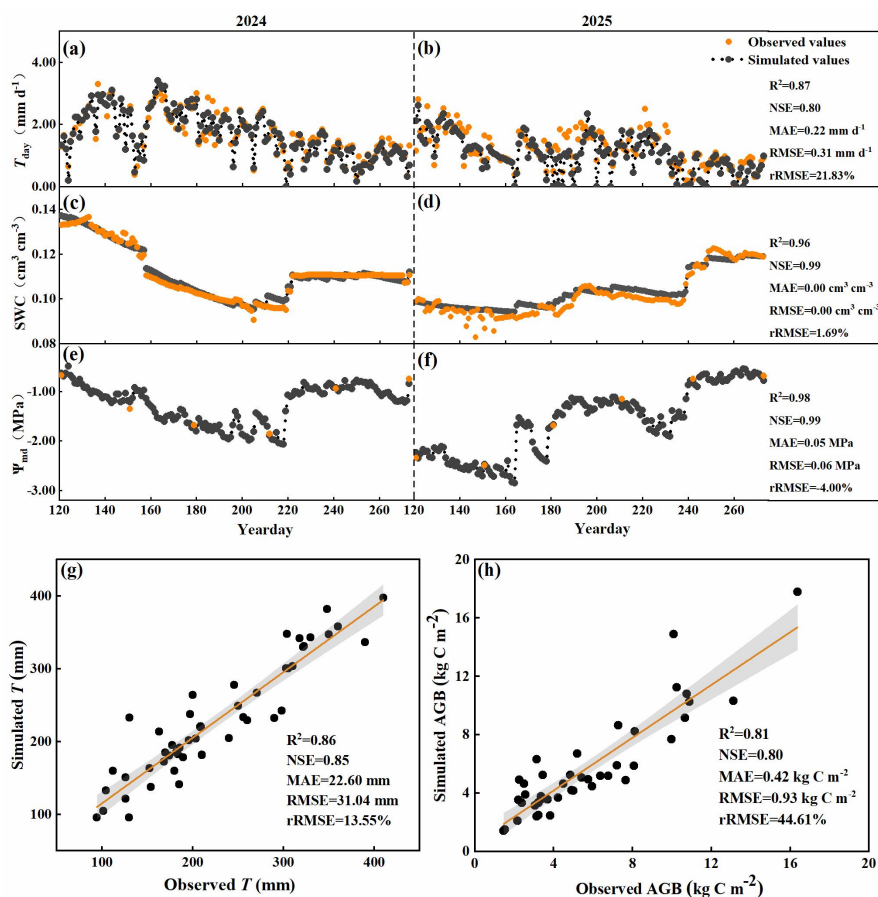
406 **3.1 BBGC-Sperry model evaluation**

407 Validation of the BBGC-Sperry model included hydraulic and growth processes.
408 Specifically, hydraulic process validation data were based on T_{day} , SWC in the 0-500
409 cm profile, and Ψ_{md} at the Ansai site during the 2024 and 2025 growing seasons (May
410 1 to September 30), as well as multi-point transpiration data during the growing season.
411 As shown in [Fig. 2a-g](#), the R^2 coefficient between the simulated and observed T_{day} was
412 0.87, with NSE, MAE, RMSE, and rRMSE values of 0.80, 0.22 mm d⁻¹, 0.31 mm d⁻¹,
413 and 21.83%, respectively. For SWC (0-500 cm), the R^2 value between the simulated
414 and observed values was 0.96, with NSE, MAE, RMSE, and rRMSE values of 0.99,
415 0.00 cm³ cm⁻³, 0.00 cm³ cm⁻³, and 1.69%, respectively. The R^2 value for Ψ_{md} between
416 the simulated and observed values was 0.98, with NSE, MAE, RMSE, and rRMSE of
417 0.99, 0.05 MPa, 0.06 MPa, and -4.00%, respectively. The R^2 between the simulated and
418 observed T was 0.86, with NSE, MAE, RMSE, and rRMSE values of 0.85, 22.60 mm,
419 31.04 mm, and 13.55%, respectively. These results indicate the BBGC-Sperry model
420 can effectively simulate dynamic changes in hydraulic processes during the growing
421 season of PT plantations on the Loess Plateau.

422 Growth process validation data were based on AGB observations from 36 sites in



423 the study area. The R^2 value between the simulated and observed AGB was 0.81, with
 424 NSE, MAE, RMSE, and rRMSE values of 0.80, 0.42 kg C m⁻², 0.93 kg C m⁻², and
 425 44.61%, respectively (Fig. 2h). These results indicate the BBGC-Sperry model can
 426 accurately simulate water transport and growth processes for PT plantations at both
 427 spatial and temporal scales. The high correlation between T, ET, AGB, and NPP
 428 indicates the BBGC-Sperry model can also effectively simulate long-term dynamic
 429 changes in NPP and ET in this region.



430
 431 **Figure. 2** Comparison of simulated and observed values for artificial *Pinus tabulaeformis*
 432 L. plantations during the growing seasons of 2024 and 2025: (a)-(b) daily transpiration



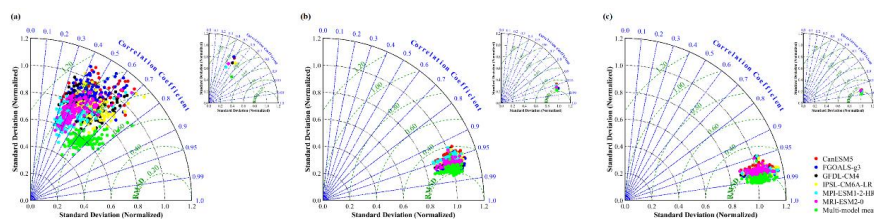
433 (T_{day}), (c)-(d) average soil water content (SWC) in the 0–500 cm soil profile, (e)-(f)
434 midday leaf water potential (Ψ_{md}), (g) multi-point transpiration during the growing
435 season (T), and (h) aboveground biomass (AGB).

436

437

438 3.2 Projected climate change

439 We validated the simulation performance of the regional climate models by comparing
440 observed climate data for the historical period (1979-2014) with the simulation results
441 from a single climate model and a multi-model average (Fig. 3). The multi-model
442 average demonstrated the best performance. Specifically, the correlation coefficient
443 between observed and simulated monthly precipitation ranged from 0.5 to 0.7 (Fig. 3),
444 while the correlation coefficients for monthly minimum and maximum temperatures
445 exceeded 0.9 (Fig. 3b, c). These results indicate these downscaled data effectively
446 represent the actual climate conditions of the study area. Therefore, multi-model
447 average climate data were employed to simulate the response of PT plantations to future
448 climate change.



449

450 **Figure. 3** Taylor diagrams of monthly precipitation (a), monthly maximum temperature
451 (b), and monthly minimum temperature (c) at 130 meteorological stations in the study
452 area from 1979 to 2014. The upper-right plot represents the mean values across all



453 stations. Each color corresponds to a climate model or multi-model ensemble. The
454 green dashed line represents the root mean square error (RMSE).

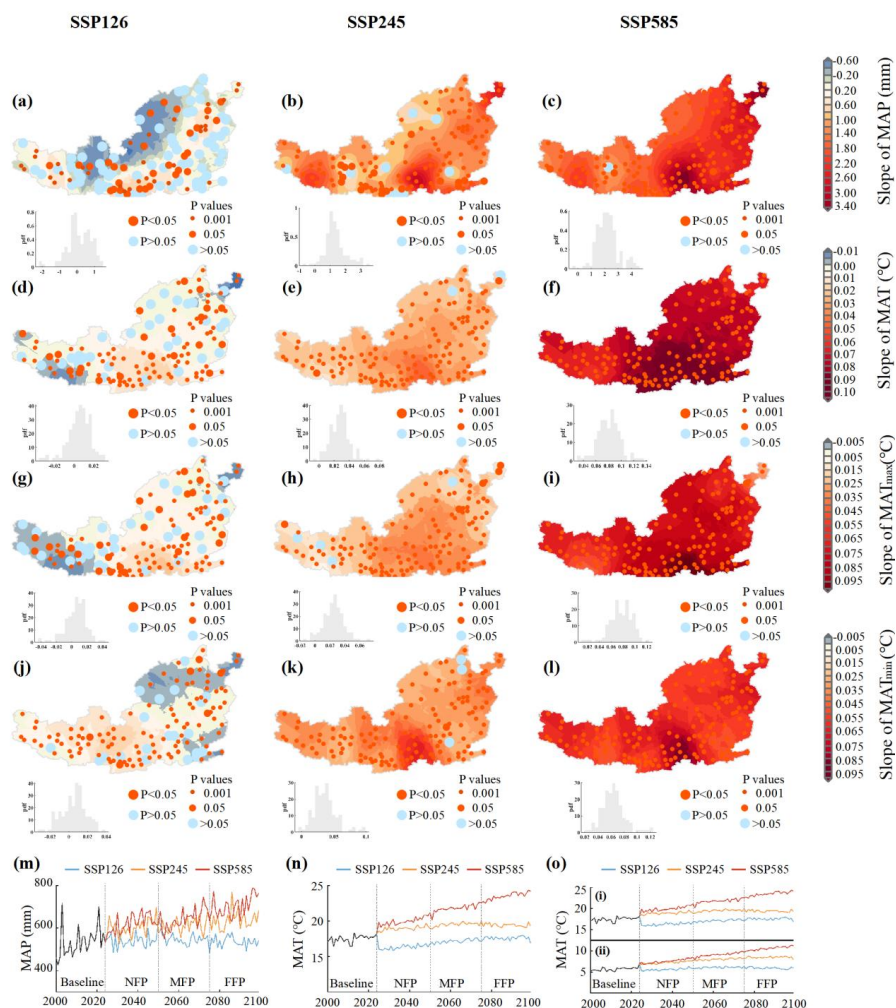
455

456 Based on the linear trends (slope values) of MAP, MAT, MAT_{max}, and MAT_{min} from
457 2000 to 2099, we analyzed the spatiotemporal changes in climate during the study
458 period (Fig. 4). The slope values of climate variables under different SSPs showed
459 significant spatial heterogeneity (Fig. 4a-l). The highest slope values were mainly
460 concentrated in the southeastern part of the study area, with a general decrease from
461 southeast to northwest. Under the SSP126 scenario, 52.9% of the region showed an
462 increasing trend in MAP during the study period, primarily in the southwest and
463 southeast, with 32.8% of the area experiencing significant increases ($p < 0.05$).
464 Conversely, decreases in MAP were mainly located in the central and northern regions.
465 MAT exhibited an increasing trend over a larger portion of the study area, covering
466 71.5%, with 58.9% of the area experiencing significant increases ($p < 0.05$). Decreases
467 in MAT were limited to the southwest and northeast regions. MAT_{max} primarily
468 increased in the central region, while decreasing regions were limited to the southwest
469 and northeast. MAT_{min} primarily increased in the western and central regions, while
470 decreasing regions were limited to the northeast and southeast. Compared to the
471 SSP126 scenario, over 95% of the study area showed increases in MAP and MAT under
472 the SSP245 and SSP585 scenarios. The areas with the largest increases were
473 concentrated in the southern part of the study area.

474 Fig. 4m-o shows future climate in the study area is expected to be warmer and



475 wetter overall compared to the baseline period. Under the SSP126 scenario, MAP
476 ranged from 482 to 633 mm, with an average increase of -0.105 mm y^{-1} . In contrast,
477 MAT ranged from 12.99 to 14.64 °C, with an average increase of 0.020 °C y^{-1} . MAT_{max}
478 ranged from 15.79 to 17.97 °C, with an average increase of 0.025 °C y^{-1} . MAT_{min} values
479 ranged from 5.21 to 6.46 °C, with an average increase of 0.007 °C y^{-1} . Under the SSP245
480 scenario, MAP values ranged from 524 to 769 mm, with an average increase of 0.77
481 mm y^{-1} . Notably, the MAP growth rate fluctuated. In contrast, MAT increased more
482 steadily, with an average increase of 0.014 °C y^{-1} for MAT, 0.010 °C y^{-1} for MAT_{max} ,
483 and 0.025 °C y^{-1} for MAT_{min} . Under the SSP585 scenario, the average increases of MAP,
484 MAT, MAT_{max} , and MAT_{min} were 1.806 mm y^{-1} , 0.070 °C y^{-1} , 0.069 °C y^{-1} , and 0.060 °C
485 y^{-1} , respectively. Overall, the FFP climate is expected to experience the most significant
486 fluctuations under the SSP585 scenario ($p < 0.05$).
487



488

489 **Figure. 4** Spatiotemporal dynamics in mean annual precipitation (MAP), mean annual
 490 temperature (MAT), mean annual maximum temperature (MAT_{max}), and mean annual
 491 minimum temperature (MAT_{min}) within the study area from 2000 to 2099 under SSP126,
 492 SSP245, and SSP585 scenarios: (a)-(l), spatial distributions of linear trend slopes for
 493 each variable under the three scenarios, with probability density functions (PDFs)
 494 shown in the lower-left corner; (m)-(o), temporal variation of MAP, MAT, MAT_{max} (i),
 495 and MAT_{min} (ii) under all SSP scenarios.

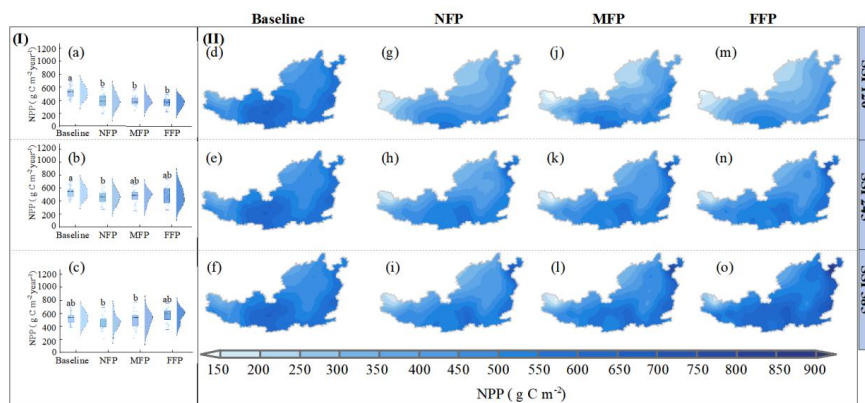


496

497 **3.3 Spatiotemporal dynamics of NPP and ET**

498 Fig. 5 shows spatiotemporal changes in the mean annual NPP of PT plantations during
 499 the baseline and future periods. The NPP of the study area was 533.5 g C m⁻² yr⁻¹ in the
 500 baseline period but significantly lower in the future periods under the SSP126 and
 501 SSP245 scenarios (Fig. 5a, b). However, the NPP in the FFP was 577.9 g C m⁻² yr⁻¹
 502 under the SSP585 scenario, which is significantly higher than in the baseline period
 503 (Fig. 5c). The highest NPP values of the baseline period were in the south and central
 504 regions, and the lowest were in the west, with a gradual decrease noted from southeast
 505 to northwest. This distribution pattern continues in the future periods.

506



507

508 **Figure. 5** Projected spatiotemporal dynamics of net primary production (NPP) for
 509 *Pinus tabuliformis* L. in the study area under baseline, SSP126, SSP245, and SSP585
 510 scenarios: (I) temporal changes in NPP, with different letters indicating significant
 511 differences among the four periods within each scenario ($p < 0.05$); (II) spatial dynamics
 512 of NPP. Baseline refers to the reference period (2000–2024), NFP to the near-future

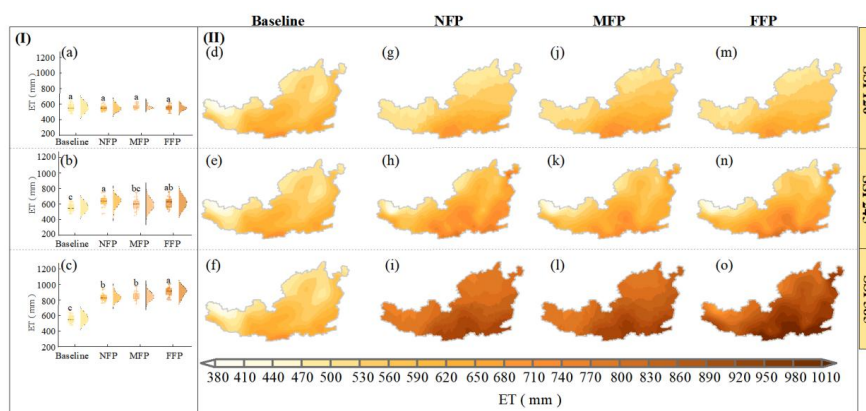


513 period (2025-2049), MFP to the mid-future period (2050-2074), and FFP to the far-
 514 future period (2075-2099).

515

516 **Fig. 6** shows the spatiotemporal changes in the mean annual ET values during the
 517 baseline and future periods. The ET was 572.9 mm during the baseline period and
 518 showed no significant changes under the SSP126 scenario in the future periods.
 519 However, it significantly increased under the SSP245 scenario and particularly under
 520 the SSP585 scenario (**Fig. 6c**). The ET value decreased gradually from southeast to
 521 northwest in the baseline period. This pattern was maintained in all SSPs.

522



523

524 **Figure. 6** Projected spatiotemporal dynamics of annual mean actual evapotranspiration
 525 (ET) for *Pinus tabuliformis* L. in the study area under baseline, SSP126, SSP245, and
 526 SSP585 scenarios: (I) temporal changes of ET, with different letters indicating
 527 significant differences among the four periods within each scenario ($p < 0.05$); (II)
 528 spatial dynamics of NPP. Baseline, NFP, MFP, and FFP are the same as defined in Fig.

529 5.

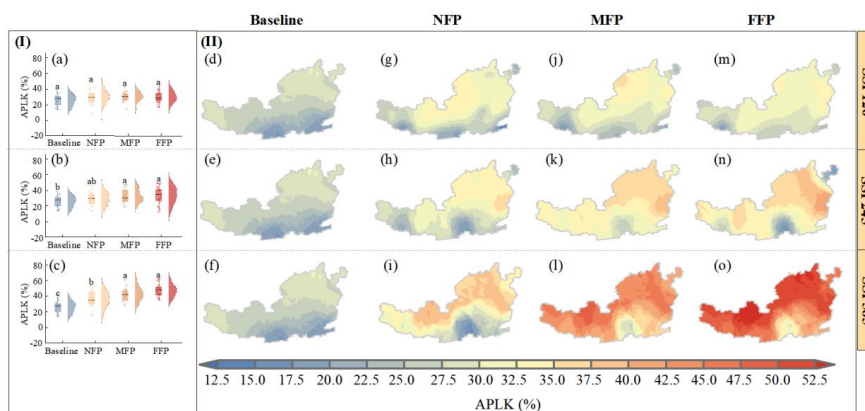


530

531 **3.4 Spatiotemporal dynamics of APLK and DMRP**

532 [Fig. 7](#) shows spatial and temporal changes in the annual APLK of PT plantations in the
533 study area during the baseline and future periods. APLK for the baseline period was
534 24.9%. Under the SSP126 scenario, APLK values in the NFP, MFP, and FFP were 28.2,
535 28.7, and 29.5%, respectively, indicating an increasing trend with a relatively slow rate
536 of change. Under the SSP245 scenario, APLK values for future periods were 29.1%
537 (NFP), 33.3% (MFP), and 32.8% (FFP), indicating a larger increase compared to the
538 baseline period. Under the SSP585 scenario, APLK values increased the most, with
539 NFP, MFP, and FFP values of 31.7%, 41.1%, and 46.4%, respectively, indicating APLK
540 values will significantly increase under a more severe climate change context. APLK
541 values during the baseline period showed an increasing trend from southeast to
542 northwest. In the future, high APLK values will gradually expand from the northwest
543 and northeast to the central and southern regions. Under the SSP585 scenario, only very
544 central and southern regions have APLK values below 35%, while most areas in the
545 central and northern regions have values above 50% in the FFP ([Fig. 7o](#)).

546



547

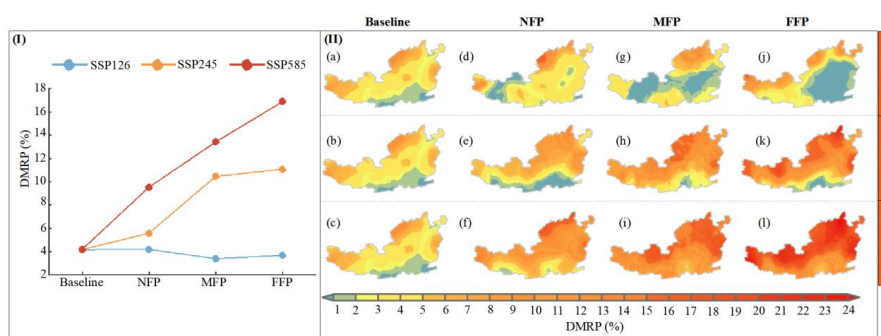
548 **Figure. 7** Projected spatiotemporal dynamics of annual average percentage loss of
 549 whole-plant hydraulic conductance (APLK) for *Pinus tabuliformis* L. in the study area
 550 under baseline, SSP126, SSP245, and SSP585 scenarios: (I) temporal changes of APLK,
 551 with different letters indicating significant differences among the four periods within
 552 each scenario ($p < 0.05$); (II) spatial dynamics of NPP. Baseline, NFP, MFP, and FFP are
 553 the same as defined in Fig. 5.

554

555 Based on a threshold of $APLK \geq 60\%$, we calculated the spatiotemporal variations
 556 of DMRP of PT plantations during the baseline and future periods (Fig. 8). Low-risk
 557 zones for DMRP were mainly located in the southern part of the study area, medium-
 558 risk zones in the central and eastern regions, and high-risk zones in the northwest, north,
 559 and east, exhibiting a clear gradient from southeast to northwest in the baseline period.
 560 Under the SSP126 scenario, the distribution of high-risk zones will be similar to the
 561 baseline period, but the distribution of low- and medium-risk zones will change. In the
 562 NFP, low-risk zones will be primarily concentrated in the west. In the MFP, low-risk
 563 zones will be primarily concentrated in the west, central, and eastern regions. In the



564 FFP, low-risk zones will be primarily concentrated in the central and eastern regions.
 565 Under the SSP245 and SSP585 scenarios, the distribution patterns of low-, medium-
 566 and high-risk zones will be similar to the baseline period but the high-risk zones will
 567 generally expand from northwest to southeast, covering a larger area. DMRP shows an
 568 increasing trend under the SSP245 and SSP585 scenarios, but a slight decreasing trend
 569 under the SSP126 scenario.
 570



571
 572 **Figure. 8** Projected spatiotemporal dynamics of drought-induced mortality risk
 573 probability (DMRP) for *Pinus tabuliformis* L. in the study area under baseline, SSP126,
 574 SSP245, and SSP585 scenarios: (I) temporal changes of DMRP; (II) spatial dynamics
 575 of DMRP. Baseline, NFP, MFP, and FFP are the same as defined in Fig. 5.

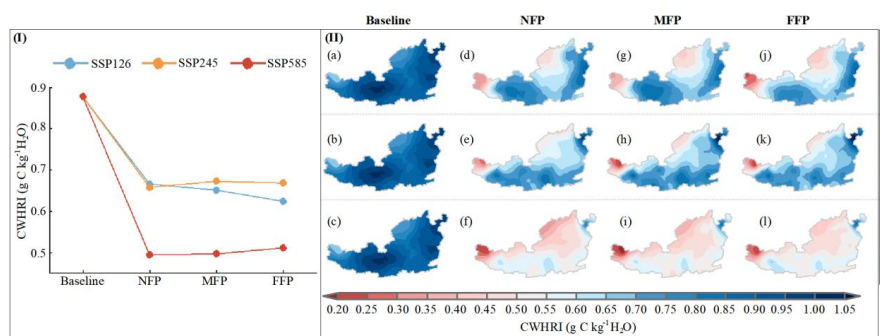
576

577 3.5 Spatiotemporal dynamics and factors influencing CWHRI

578 To comprehensively assess the growth of PT plantations, NPP, ET, and DMRP were
 579 used to calculate the CWHRI (Fig. 9). The CWHRI during the baseline period was 0.89
 580 g C kg⁻¹ H₂O and will decrease under the SSP126, SSP245, and SSP585 scenarios to
 581 0.63-0.67, 0.66-0.67, and 0.50-0.51 g C kg⁻¹ H₂O, respectively. This indicates the



582 growth of PT plantations will be retarded in the future and more susceptible to hydraulic
 583 failure and even death. CWHRI showed considerable spatial variability, with low-value
 584 zones mainly located in the western and northern parts of the study area, showing a
 585 distinct decreasing gradient from southeast to northwest in the baseline period. This
 586 pattern was maintained in all SSPs. Generally, areas with low CWHRI values will
 587 expand in the future periods. Under the SSP585 scenario, the CWHRI in the western
 588 parts of the study area will even fall below 0.25 g C kg⁻¹ H₂O. This suggests PT
 589 plantations in the western and northern parts of the study area will find it even more
 590 challenging to survive.
 591



592
 593 **Figure. 9** Projected spatiotemporal dynamics of the carbon-water-hydraulic risk index
 594 (CWHRI) for *Pinus tabuliformis* L. in the study area under baseline, SSP126, SSP245,
 595 and SSP585 scenarios: (I) temporal changes of CWHRI; (II) spatial dynamics of
 596 CWHRI. Baseline, NFP, MFP, and FFP are the same as defined in Fig. 5.

597
 598 To quantify the extent to which NPP, ET, and DMRP influence changes in the
 599 CWHRI, we used multiple linear regression to calculate the relative contribution of



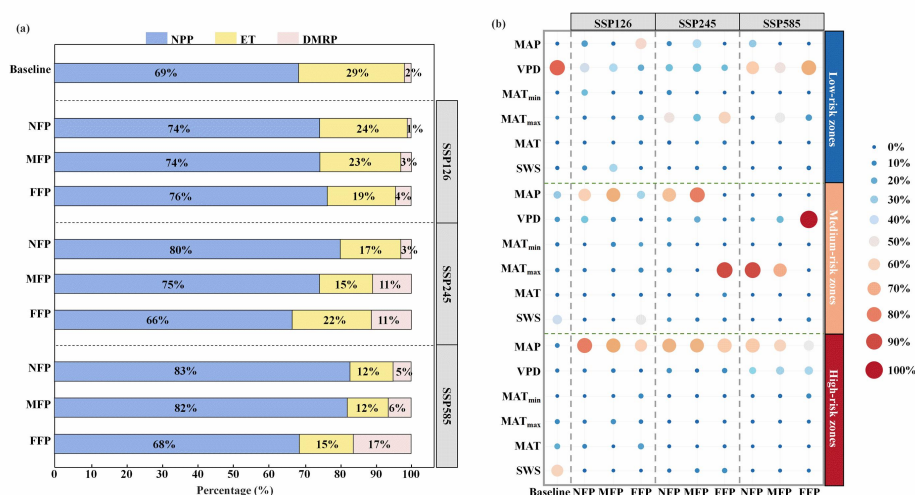
600 each variable (Fig. 10a). During the baseline period, net NPP and ET can explain 98%
601 of the variation in CWHRI. NPP and ET remain the main factors affecting CWHRI in
602 the future; however, the contribution of DMRP will continue to increase in all SSPs
603 over the three future periods, reaching 17% in the FFP under the SSP585 scenario.

604 To deepen understanding of the factors driving CWHRI and how the relative
605 importance of these factors changes, Fig. 10b presents an XGBoost-based assessment
606 of the relative importance of six environmental factors for regions with different risk
607 levels during the baseline and future periods. In the baseline period, VPD and SWS
608 ranked as the top contributors. Specifically, the relative importance of VPD was 86%
609 in the low-risk zones, and of SWS was 42% and 61% in the medium- and high-risk
610 zones, respectively. Under the SSP126 scenario, VPD will remain the primary factor
611 but its relative importance will decrease by 49% and 59% in the low-risk zones during
612 the NFP and MFP, respectively. MAP will rank as the top contributor in the low-risk
613 zones during the FFP, with a relative importance of 56%. In the medium-risk zones,
614 MAP will be the primary factor during the NFP and MFP. SWS will be the main factor
615 during the FFP, similar to the baseline period. In high-risk zones, MAP will be the main
616 factor in all three periods, with relative importance ranging from 62% to 81%. Under
617 the SSP245 scenario, MAT_{max} will be the main factor in the NFP and FFP in low-risk
618 zones, with a relative importance of 51% and 60%, respectively. MAP, VPD and
619 MAT_{max} will rank as the top contributors in the MFP, with the relative importance of
620 these three factors being 91%. In the medium-risk zones, MAP will be the main factor
621 in the NFP and MFP, while MAT_{max} will be the main factor in the FFP. In high-risk



622 zones, MAP will be the main factor in all three periods, with relative importance
 623 ranging from 67% to 76%. Under the SSP585 scenario, VPD will be the primary factor
 624 in low-risk zones during all three future periods, with a relative importance over 50%.
 625 In medium-risk zones, MAT_{max} will be the primary factor during the NFP and MFP,
 626 with a relative importance over 70%. VPD will be the primary factor during the FFP,
 627 with a relative importance of 99% highlighting the strong sensitivity of the CWHRI to
 628 atmospheric drought in the FFP. In high-risk zones, MAP will be the main factor in all
 629 three periods, with relative importance ranging from 49% to 68%. Generally, the
 630 relative importance of MAP and MAT_{max} will increase from the baseline period into
 631 the future, reflecting the moisture- and temperature-driven characteristics of the
 632 CWHRI under future climate change.

633



634

635 **Figure. 10** Analysis of factors influencing variation in the carbon-water-hydraulic risk

636 index (CWHRI): (a) contributions of net primary productivity (NPP), ecosystem



637 evapotranspiration (ET), and drought-induced mortality risk (DMRP) as determined by
638 multiple linear regression analysis; (b) analysis of the relative importance of six
639 environmental variables. MAP, mean annual precipitation; MAT mean annual
640 temperature; MAT_{max} , mean annual maximum temperature; MAT_{min} , mean annual
641 minimum temperature; VPD, mean annual vapor pressure deficit, SWS, mean annual
642 soil water storage. Low-risk zones, $DMRP < 2\%$. Medium-risk zones, $2\% \leq DMRP \leq$
643 5% . High-risk zones, $DMRP > 5\%$.

644

645 **4 Discussion**

646 **4.1 BBGC-Sperry Model performance**

647 The BBGC-Sperry model is a coupled model. Therefore, a thorough validation is
648 essential when using this model for simulation and prediction (Yan et al., 2022).
649 Transpiration, SWC, Ψ_{md} , and AGB are critical indicators for assessing the complex
650 effects of climate change on vegetation growth and physiological characteristics.
651 Accordingly, we validated the reliability of the BBGC-Sperry model in simulating the
652 growth dynamics of PT plantations by using data from 36 meteorological stations on
653 the Loess Plateau (Fig. 2). The results indicate R^2 and NSE values for all simulated and
654 measured indicators exceed 0.8, demonstrating the model effectively captures the
655 dynamic changes in growth and ecohydrological processes in the PT plantations. This
656 ability is closely tied to the model structure and input parameters.

657 The Sperry model replaces the SPAC water transport module of the original Biome-
658 BGC model with an improved soil moisture transport module developed by Huang et



659 [al. \(2013\)](#). This allows for greater control over dynamic changes in plant hydraulic traits
660 and enables the simulation of interactions among the water, carbon, and nitrogen cycles.
661 The BBGC-Sperry model provides a more refined simulation of vegetation growth
662 processes and physiological mechanisms than the original model, and has been
663 successfully applied to the Loess Plateau ([Zhang et al., 2020, 2024b](#); [Yan et al., 2022](#)).
664 Meteorological parameters were sourced from continuous observational data, and soil
665 and vegetation physiological parameters were derived from field measurements or
666 published literature, thereby ensuring the accuracy of the validation process.

667 **4.2 Changes of NPP, ET and DMRP for *Pinus tabuliformis* L. plantation**

668 Against the backdrop of global warming, the study area is projected to become
669 generally warmer and wetter in the future. Particularly under the SSP245 and SSP585
670 scenarios, average temperatures and precipitation will increase. These findings are
671 consistent with previous studies ([Xu et al., 2024](#)). An assessment of the growth status
672 of planted forests must not only consider their carbon sequestration capacity but also
673 involve a comprehensive evaluation of related water fluxes and transport processes.
674 Especially in water-scarce regions, water availability is the primary factor limiting the
675 growth of planted forests. Considerable research shows that relying solely on indicators
676 such as leaf area index, carbon sequestration, and ET to assess vegetation growth is
677 insufficient as these superficial indicators may mask the physiological stress
678 experienced by the vegetation ([Tang et al., 2026](#)).

679 Thus, we used the BBGC-Sperry model not only to simulate carbon and water
680 fluxes of the PT plantations in the study area ([Fig.s 5 and 6](#)) but also to simulate



681 indicators that reflect vegetation physiology (Fig.s 7 and 8). The results show NPP in
682 the study area will, in general, significantly decrease compared to the baseline period
683 while the ET, APLK, and DMRP will significantly increase. Precipitation, temperature,
684 and carbon dioxide concentrations all significantly impact NPP. Previous studies show
685 increasing precipitation generally improves the water-use efficiency of vegetation and
686 that moderate temperature increases and rising carbon dioxide concentrations promote
687 photosynthesis. However, rising temperatures will decrease precipitation-use efficiency,
688 thereby negatively impacting NPP (Gong et al., 2026). At the same time, high
689 temperatures can inhibit the opening of plant stomata, thereby reducing plant
690 productivity (He et al., 2024). Furthermore, NPP shows an upward trend across all three
691 periods under all SSPs considered. This is primarily due to increased precipitation and
692 carbon dioxide concentrations, which promote vegetation growth (Walker et al., 2021;
693 Yan et al., 2022; Ouyang et al., 2014). ET is also projected to trend upward due to the
694 combined effects of increased precipitation and rising temperatures. Precipitation
695 serves as a source of water for ET. Rising temperatures prolong ET, thereby directly
696 increasing atmospheric water demand and promoting the transfer of more water from
697 the soil and vegetation into the air. Chai et al. (2025) and Lu et al. (2025) also reported
698 this phenomenon.

699 These macroscopic observations reveal profound changes in plant hydraulic
700 mechanisms. As climate change intensifies from the baseline period to the SSP126,
701 SSP245, and SSP585 scenarios, rising temperatures combined with increased potential
702 ET trigger mechanisms of plant hydraulic failure, as evidenced by significant increases



703 in APLK and DMRP. The intensification of hydraulic failure leads to a decline in
704 stomatal conductance, which in turn impairs cell turgor, membrane permeability, and
705 xylem conduction, significantly increasing plant vulnerability to heat stress and
706 outbreaks of pests and diseases (Torres-Ruiz et al., 2024). This ultimately results in
707 limited photosynthetic rates and a significant decline in productivity. The findings from
708 this study are consistent with previous research. Bonal et al. (2016) pointed out that tree
709 mortality caused by drought and high temperatures not only reduces regional NPP but
710 also weakens the cooling effect of ET, thereby creating a positive feedback loop that
711 exacerbates global warming. Choat et al. (2018) further found that even a slight increase
712 in temperature may result in hydraulic imbalance or even death for most tree species.
713 Notably, NPP, ET, and DMRP all show a synchronous increase in the FFP under the
714 SSP585 scenario. This phenomenon may be attributed to the fact that, under extreme
715 conditions, the offsetting effect of greater precipitation and CO₂ fertilization under
716 SSP585, exceeding warming-induced productivity suppression. (Walker et al., 2021;
717 Yan et al., 2022; Ouyang et al., 2014). Although we observe an increase in carbon
718 accumulation, the internal physiological stress the plants endure also significantly
719 increases. The above results indicate that relying solely on macroscopic indicators is
720 insufficient to capture the true growth state of vegetation. Therefore, a comprehensive
721 assessment method that incorporates water transport processes is of great significance
722 for accurately predicting vegetation growth dynamics and stability under future climate
723 change.

724 4.3 Changes of CWHRI for *Pinus tabuliformis* L. plantation



725 In this study, we further calculated the CWHRI based on the three fundamental
726 indicators (NPP, ET, and DMRP) (Fig. 9). Compared to the baseline period, the CWHRI
727 will significantly decline in the future, indicating PT plantation sustainability will face
728 severe constraints. The greater fluctuations in NPP during the study period are the
729 dominant factor affecting the CWHRI, but the relative importance of DMRP has been
730 steadily increasing under all SSPs, rising from 2% during the baseline period to 17% in
731 the FFP under SSP585. This increasing contribution indicates that although
732 conventional water-use efficiency adequately characterizes carbon-water relationships
733 under current and near-term conditions, failure to account for the increasing influence
734 of hydraulic failure risk may lead to progressively optimistic estimates of long-term
735 plantation sustainability. And this bias likely to accumulate over time. These findings
736 also corroborate the concerns raised by Wang et al. (2025) regarding future vegetation
737 growth.

738 The primary environmental factors influencing the CWHRI are related to the
739 availability of water resources. During the baseline period, MAP, VPD, and SWS were
740 the primary driving factors. In all SSPs, the importance of MAP and MAT_{max} increases,
741 with these becoming the most significant drivers. SWS directly determines the amount
742 of water available to vegetation, while MAT_{max} and VPD are related not only to the
743 degree of environmental aridity but also the stomatal conductance of vegetation and
744 upward water transport driven by transpiration (Wang et al., 2009; Wang et al., 2024;
745 Tang et al., 2026). Therefore, these factors strongly influence the variability of CWHRI.
746 These findings indicate water-related ecological factors and meteorological variables



747 remain key elements for future model improvements and ecological management
748 strategies. Furthermore, the CWHRI declines steadily from the baseline period to the
749 future periods, underscoring the urgency to formulate new management strategies and
750 implement proactive intervention measures.

751 **4.4 Limitations and implications**

752 This study used the eco-hydrological BBGC-Sperry model to predict the growth, water
753 consumption, and drought-induced mortality risk of PT plantations under future climate
754 scenarios. The vegetation parameters in this model are fixed, which typically implies
755 the spatiotemporal variability of vegetation growth is ignored, thereby introducing
756 uncertainty into the simulation results. Recent studies based on the theory of plant
757 hydraulic adaptation have predicted plant hydraulic, stomatal, and photosynthetic traits
758 across various spatiotemporal scales (Joshi et al., 2022; Sperry et al., 2019). Future
759 research should focus on integrating vegetation growth dynamics to further enhance
760 model calibration and accuracy. We used meteorological data with a resolution of 0.25° ,
761 which effectively captures the dynamics of future climate change. However, limitations
762 in accuracy may persist, particularly in precipitation prediction, which has notably
763 lower accuracy. Spatially, we extended the simulated data from 130 meteorological
764 stations across the region using Kriging interpolation. Although this method is
765 computationally efficient, it may have limitations in resolution and accuracy.
766 Additionally, although the BBGC-Sperry model has improved accuracy for simulating
767 hydraulic transport processes compared to the original Biome-BGC model, the recently
768 introduced BBGCMuSo model has more comprehensively simulated management



769 practices. These improvements need to be integrated into the BBGC-Sperry model to
770 better analyze the ability of different management strategies to improve the
771 sustainability of forest plantations.

772 Despite certain methodological limitations, this study provides valuable scientific
773 insights for the sustainable development of PT plantations. Compared to previous
774 simulations, our study offers a comprehensive explanation of the drought response
775 mechanisms of PT plantations under future climate change. Notably, under the
776 backdrop of global climate change, the CWHRI of plantations is projected decline and
777 the contribution of DMRP has been steadily increasing under all SSPs, which indicated
778 that current forest management practices may render years of restoration efforts
779 ineffective. We recommend accurately assessing the optimal vegetation cover using soil
780 moisture carrying capacity thresholds or early-warning models, implementing thinning
781 management for existing PT plantations, as well as mixed-species planting in low-risk
782 southeastern regions, slope engineering practices in moderate-risk central and western
783 regions (Yang et al., 2023), and gradually converting plantations to drought-tolerant
784 shrubs or sparse grasslands in high-risk northwestern regions, to increase plantation
785 sustainability and enable proactive responses to future global climate change.

786

787 **5 Conclusion**

788 This study used the BBGC-Sperry model to simulate the spatiotemporal dynamics of
789 PT plantations from 2000 to 2099 under future climate scenarios (SSP126, SSP245,
790 SSP585) on the Loess Plateau. The key findings are as follows:



791 (1) The BBGC-Sperry model, verified using hydraulic and growth process data,
792 can effectively simulate the growth of PT plantations and their drought-induced
793 mortality risk probability.

794 (2) The growth of PT plantations will slow down in the future. During the 100-year
795 period, NPP values of PT plantations are projected to significantly decline, except in
796 the FFP under the SSP585 scenario. Overall, spatial change patterns reveal a gradual
797 decline in vegetation growth from the southeast to northwest. ET is projected to show
798 the opposite trend.

799 (3) The mortality risk for PT plantations will increase, and the affected area will
800 also expand. The APLK and DMRP of PT plantations are projected to significantly
801 increase in the future. The study area will gradually shift from low-to-medium risk areas
802 in the southeast to medium-to-high risk areas in the northwest.

803 (4) Compared to the baseline period, the CWHSI of PT plantations is projected to
804 significantly decline in the future. The contribution of DMRP to CWHRI variability
805 rises steadily across all SSPs, indicating that hydraulic risk constitutes a key constraint
806 on plantation sustainability under future climate change.

807 These findings provide a better understanding of the growth of PT plantations in
808 the restoration areas and how they will respond to future climate change. These results
809 suggest that assessments neglecting plant hydraulic risk may overestimate future
810 plantation persistence, and highlight the importance of prioritizing hydraulic safety and
811 tree survival in future plantation management.



812 **Data availability**

813 Data will be made available on request.

814

815 **Author contributions**

816 **Tianqi Guo:** Writing – original draft, Software, Methodology, Formal analysis, Data

817 curation, Conceptualization.

818 **Mingbin Huang:** Writing – review & editing, Supervision, Project administration,

819 Methodology, Funding acquisition, Conceptualization.

820 **Zhongdian Zhang:** Writing – review & editing.

821 **Rui Liu:** Writing – review & editing, Data curation.

822 **Xiaofei Wu:** Data curation.

823 **Xinmei Liu:** Writing – review.

824 **Chenyi Ju:** Writing – review.

825

826 **Competing interests**

827 The authors declare that they have no known competing financial interests or personal

828 relationships that could have appeared to influence the work reported in this paper.

829

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