



21 **Abstract.** Land use change, particularly deforestation, significantly influences the global
22 climate system. While various studies have explored how deforestation affects temperature and
23 precipitation, its impact on drought remains less explored. Understanding these effects across
24 different climate zones and time scales is crucial for crafting effective land use policies aimed
25 at mitigating climate change. This study seeks to investigate how changes in forest cover affect
26 drought across different time scales and climate zones using simulated deforestation scenarios,
27 where forests are converted to grasslands. The study utilizes data from nine global climate
28 models participating in the Land Use Model Intercomparison Project. Drought effects are
29 assessed by examining changes in the Standardized Precipitation Evapotranspiration Index
30 (SPEI). The results reveal that deforestation leads to negative shifts in global SPEIs, indicating
31 increased dryness, particularly in tropical regions, while causing wetter conditions in dry
32 regions. Moreover, the impact on drought indices becomes more pronounced with longer time
33 scales, underscoring the lasting effects of deforestation on drought. Seasonally, deforestation
34 exacerbates SPEI03 shifts during autumn and winter, especially affecting tropical and northern
35 polar regions. Continental zones experience significant seasonal changes, becoming drier in
36 winter and wetter in summer due to global deforestation, while the northern hemisphere's dry
37 regions see increased wetter conditions, particularly in autumn. These findings deepen our
38 understanding of the relationship between vegetation change and climate change, offering
39 valuable insights for better resource management and mitigation strategies against future
40 climate change impacts.

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42

43 **1. Introduction**

44 Forests cover approximately 30% of the global ice-free land surface and are distributed widely
45 from the tropics to boreal regions (Crowther et al., 2015; Hansen et al., 2013). Forests are one
46 of the largest carbon storages on the planet and play a crucial role in regulating the Earth's
47 climate (Bonan, 2008; Pan et al., 2011). However, global forests are rapidly changing due to a
48 variety of human activities, including deforestation, forest degradation, and climate change
49 effects (Hansen et al., 2013; Keenan et al., 2015; Forzieri et al., 2021). In the tropics,
50 deforestation and conversion to agriculture (mainly pasture) or other land uses are the primary
51 drivers of forest loss (Vancutsem et al., 2021). In temperate and boreal regions, forest cover
52 disturbances are often driven by logging and natural disturbances (fires, pests, or wind



53 outbreaks) (Ceccherini et al., 2020; Seidl et al., 2017). These changes can have significant
54 impacts on local and global climate patterns by altering both biogeochemical and
55 biogeophysical processes (Bonan, 2008; Jia et al., 2022). Biogeochemical processes refer to
56 the exchange of gases and particles between the atmosphere and forest ecosystems, such as the
57 absorption and release of carbon dioxide and other greenhouse gases. Biogeophysical processes
58 encompass modifications in surface energy balance, including the reflection of sunlight,
59 evapotranspiration, and heat exchange between the land and atmosphere. The loss of forest
60 cover can alter biogeochemical processes by reducing the amount of carbon dioxide stored in
61 vegetation and increasing greenhouse gas concentrations in the atmosphere (Harris et al.,
62 2012). Deforestation induces changes in biogeophysical processes, such as increased surface
63 albedo and reduced surface roughness and evapotranspiration, which result in changes to
64 regional climate patterns (Alkama and Cescatti, 2016; Bonan, 2008; Davidson et al., 2012).

65 An increasing amount of observational and modelling studies show that alterations of
66 forest cover have a significant influence on the climate system (Douville et al., 2021; Jia et al.,
67 2022). The effects are highly spatially heterogeneous. In the tropical region, large scale
68 deforestation can lead to a decline in annual total precipitation of approximately 30% (Snyder
69 et al., 2004; Perugini et al., 2017), although the streamflow in the deforested area can increase
70 (Taylor et al., 2022; Douville et al., 2021), and to an increase in temperatures of around $0.41 \pm$
71 $0.57 \text{ }^\circ\text{C}$ or $0.60 \pm 0.74 \text{ }^\circ\text{C}$ according to observational or modelling studies, respectively
72 (Alkama and Cescatti, 2016; Perugini et al., 2017). At the same time, small scale deforestation
73 in the tropics may increase precipitation locally (Lawrence and Vandecar, 2014; Douville et
74 al., 2021). In the boreal region, the conversion of forests to bare land or grassland can lead to
75 land surface cooling of $-0.41 \pm 0.57 \text{ }^\circ\text{C}$ (observational studies) or $-2.18 \pm 1.08 \text{ }^\circ\text{C}$ (modelling
76 studies) (Perugini et al., 2017). There may also be a slight reduction in precipitation following
77 deforestation in the boreal region (Perugini et al., 2017; Cherubini et al., 2018). In the temperate
78 area, the impacts of forest change on temperature and precipitation are more uncertain and
79 variable across regions. Mahmood et al. (2014) found that deforestation can lead to both
80 warming and cooling effects depending on the region, and Findell et al. (2017) noted that the
81 spatial variability of the impacts on temperature is high. Observational studies suggest an
82 annual mean warming of $0.50 \text{ }^\circ\text{C}$ following deforestation in temperate regions while modelling
83 studies indicate an average annual cooling of $-0.73 \pm 0.45 \text{ }^\circ\text{C}$ (Perugini et al., 2017). Detecting
84 the signal of forest cover changes on precipitation in the temperate region is challenging due
85 to the high variability of synoptic scale meteorological systems that impact local-to-regional
86 circulation and rainfall patterns (Bala et al., 2007; Bonan, 2008; Field et al., 2007).



87 Climate models are a valuable tool for investigating the impact of changes in forest cover
88 on the climate system. However, the results of modelling studies are variable and model-
89 dependent, and a wide range of estimated effects is usually observed. For instance, in the boreal
90 region, the cooling effect of forest change on the surface air temperature ranges from -4.0 to -
91 0.81 °C, depending on the specific model used, the parameters used to represent forest cover,
92 the region where the replacement of land cover occurs, and the type of land cover conversion
93 considered (Perugini et al., 2017). To facilitate a consensus on forest management decisions,
94 the climate and ecology communities are working towards establishing a unified framework
95 with standardized settings for assessing forest change impacts. The Land Use Model
96 Intercomparison Project (LUMIP) (Lawrence et al., 2016), a component of the Coupled Model
97 Intercomparison Project Phase 6 (CMIP6) (Eyring et al., 2016), is a prominent example of such
98 an effort. LUMIP aims to address key scientific questions related to the impacts of land use on
99 climate (Lawrence et al., 2016). The idealized coupled deforestation experiment (*deforest-
100 global*) is a specific experiment within LUMIP that focuses on the global biogeophysical and
101 biogeochemical impacts of deforestation on climate. To ensure comparability between models,
102 participating models were required to use a similar deforestation pattern, even if they employ
103 different variables to represent the deforestation signal (Lawrence et al., 2016). Researchers
104 utilized the datasets from LUMIP to examine the responses of temperature (Boysen et al.,
105 2020), precipitation (Boysen et al., 2020; Luo et al., 2022), and carbon storage (Ito et al., 2020;
106 Li et al., 2022) from global deforestation at both the global and regional scales.

107 Previous studies primarily focused on the biogeophysical effect of forest change on
108 individual climate variables such as temperature and precipitation, without considering the
109 potential impact on meteorological drought conditions (hereafter referred to drought), which
110 are of greater relevance to decision-makers in shaping policies for sustainable land use and
111 water management. However, changes in temperature and precipitation can have significant
112 effects on drought, a natural hazard that has caused extensive economic and social damage
113 worldwide. Drought is characterized by below-normal rainfall over a period of months to years
114 (Dai, 2011) and is mainly driven by the combined effect of temperature, precipitation, wind
115 speed, and solar radiation (Seneviratne, 2012). Understanding the behavior of droughts is
116 essential for better water resource management and planning. In addition to human wellbeing,
117 it poses a serious threat to ecosystems by altering soil moisture, forest structure and carbon
118 content (Nepstad et al., 2007). While several studies have explored the impact of deforestation
119 on regional drought conditions, these have primarily focused on the Amazon region. For
120 instance, deforestation can lead to less water being recycled, thereby intensifying regional dry



121 seasons (Bagley et al., 2014; Staal et al., 2020), and converting mid-latitude natural forests to
122 cropland and pastures may increase the frequency of hot-dry summers (Findell et al., 2017).
123 Furthermore, forest cover change can modulate the impacts of precipitation and temperature
124 on drought (Li et al., 2024). The impact of forest changes on drought conditions across different
125 regions and time scales remains largely unexplored.

126 The main focus of our study is to analyze the response of droughts to deforestation using
127 idealized experiments with data from nine LUMIP models. We aim to address several key
128 scientific questions related to this topic:

129 1. What are the global and regional-scale responses of droughts to idealized deforestation?
130 By examining the effects of deforestation on drought conditions, we aim to gain insights into
131 how changes in forest cover impact drought patterns on a broader scale.

132 2. How does the response of drought vary across different climate zones and time scales?
133 We will investigate whether the influence of deforestation on droughts differs depending on
134 the location and time scales. This analysis will help us understand the temporal dynamics of
135 drought response to changes in forest cover.

136 3. Does short-term drought exhibit seasonal characteristics in response to changes in forest
137 cover? We will explore whether the impact of deforestation on droughts shows a seasonal
138 pattern, particularly in the context of short-term drought events. Understanding seasonal
139 variations in the response of drought to forest cover changes can provide valuable insights for
140 managing and mitigating drought risks.

141 Through our study, we aim to contribute to the scientific understanding of the complex
142 relationship between deforestation and droughts, shedding light on the spatial and temporal
143 aspects of this interaction. By addressing these scientific questions, we hope to provide
144 valuable insights for policymakers and land managers in formulating effective strategies for
145 drought mitigation and adaptation. This information can also be used to inform forest
146 management decisions aimed at mitigating the negative impacts of deforestation on water
147 resources and ecosystems. The paper is structured as follows: Section 1 presents a brief
148 introduction, while Section 2 provides an overview of the methods and datasets used, including
149 the experiment design, model introduction, drought index used, climate zoning basis, and the
150 evaluation of the effect. Section 3 analyzes the changes in meteorological factors (temperature
151 and precipitation) and droughts in response to deforestation, specifically exploring how
152 droughts respond in different climate zones and time scales, as well as seasonal changes in



153 short-term drought. Section 4 discusses the limitations and potential avenues for future
154 research, and Section 5 summarizes the main conclusions.

155 **2. Method and Data**

156 **2.1 Experiment design and introduction of models**

157 Two experiments from LUMIP are used in this study, i.e. *piControl* and *deforest-global*. The
158 *piControl* experiment is a standard control experiment, with spatial resolution ranging from
159 $0.7^\circ \times 0.7^\circ$ to $2.8^\circ \times 2.8^\circ$ (depending on the model) and at 15 to 60 minutes time step, that is
160 designed to provide a reference state for climate models. It is typically run for several hundred
161 years to ensure that the model reaches a steady state, and is used to evaluate the performance
162 of the model (Eyring et al., 2016). The *deforest-global* experiment is an idealized experiment
163 designed to investigate the effects of global deforestation on climate. It is branched from the
164 *piControl* experiment and uses the same forcing, including CO₂ concentration, land-use maps,
165 and land management (Lawrence et al., 2016). The *deforest-global* experimental design
166 involves sorting land grid cells based on their forest area in 1850 and selecting the top 30% of
167 grid cells for tree replacement and calculating tree plant type loss for each year at each grid cell
168 by attributing the 0.4 Mkm² per year forest loss proportionally to their forest cover fraction
169 across the forest replacement grid cells. Therefore, total 20 Mkm² of the forest is replaced by
170 grassland in a linear fashion over 50 years. After forest replacement, the ground biomass is
171 removed, and the underground biomass is changed to litter pools. The dynamic vegetation
172 modules can be closed over the deforestation grids to ensure the proper process of carbon
173 transition, while outside of the deforestation grids, the dynamic vegetation modules can be kept
174 because the impact of climate change caused by deforestation on tree fraction is small.

175 Several climate variables are needed to calculate the drought index including
176 temperature, precipitation, wind speeds, etc (see details in Table S1 in Supplemental Material).
177 There are nine models covering these variables including BCC-CSM2-MR (Wu et al., 2019),
178 CMCC-ESM2 (Lovato et al., 2022), CNRM-ESM2-1 (Séférian et al., 2019), CanESM5 (Swart
179 et al., 2019), EC-Earth3-Veg (Döscher et al., 2022), GISS-E2-1-G (Kelley et al., 2020), IPSL-
180 CM6A-LR (Boucher et al., 2020), MIROC-ES2L (Hajima et al., 2020) and UKESM1-0-LL
181 (Sellar et al., 2020). More information regarding the deforestation simulation and the land
182 surface model for each Earth system model can be found in Table S2 and Supplementary Text
183 1. All simulation datasets for both the *piControl* and *deforest-global* experiments can be



184 downloaded from the Earth System Grid Federation (ESGF) at <https://esgf->
185 node.llnl.gov/search/cmip6/ (last accessed 6 March 2023) (Balaji et al., 2018). Most models
186 have only one run member, with the exception of IPSL-CM6A-LR, which has three run
187 members. To ensure consistency in the results, we selected the first run for all models in our
188 analysis. As the datasets have varying spatial resolutions, they were interpolated to the N48 lat-
189 lon resolution (i.e. $1.875^\circ \times 1.875^\circ$) by using bilinear interpolation.

190 **2.2 Introduction of the drought index**

191 In this study, we use the SPEI (Standardized Precipitation Evapotranspiration Index) to
192 characterize drought, which is well established in the literature (Vicente-Serrano et al., 2010).
193 Table S1 in the Supplementary lists the climate variables necessary to compute the SPEI. The
194 SPEI is an extension of the Standardized Precipitation Index (SPI), which maps precipitation
195 intensity onto a standard Gaussian variable and is based solely on precipitation amounts
196 (McKee et al., 1993). Compared to SPI, the SPEI additionally takes the influence of potential
197 evapotranspiration (*PET*) into account, which refers to the amount of water that could
198 evaporate and transpire under specific environmental conditions if water availability is not a
199 limiting factor. This makes the SPEI a more comprehensive measure of drought than the SPI.
200 The water deficit (D_i) for month i is defined by

$$201 \quad D_i = Pr_i - PET_i, \quad (1)$$

202 Similar to the calculation of SPI, D_i can be aggregated for the desired time scales, e.g.
203 for k month. The aggregated D_i for k months is the series D_i^k . The log-logistic distribution has
204 been selected as the most appropriate statistical model to characterize D_i^k . Subsequently, the
205 standardized D_i^k values are derived from this distribution to calculate the SPEI (Vicente-Serrano et
206 al., 2010). The probability density function $f(D_i^k)$ and the probability distribution function
207 $F(D_i^k)$ for the D_i^k are expressed as

$$208 \quad f(D_i^k) = \frac{\beta}{\alpha} \left(\frac{D_i^k - \gamma}{\alpha}\right)^{\beta-1} \left(1 + \left(\frac{D_i^k - \gamma}{\alpha}\right)^\beta\right)^{-2} \quad (2)$$

$$209 \quad F(D_i^k) = \left(1 + \left(\frac{\alpha}{D_i^k - \gamma}\right)^\beta\right)^{-1} \quad (3)$$

210 where α , β and γ denote the scale, shape and origin parameter, respectively. These
211 parameters (α , β and γ) can be estimated using unbiased probability weighted moments ('ub-
212 pwm'), plotting-position PWM ('pp-pwm'), or maximum likelihood ('max-lik'). After



213 estimating parameters (α , β and γ) based on observed or climate model derived values of D_i^k ,
214 the probability distribution function $F(D_i^k)$ can be computed for each D_i^k . Using the
215 equiprobability transformation (Panofsky and Brier, 1968), the probability distribution
216 function is then transformed into a standardized normal random variable with a zero mean and
217 unit variance. The resulting standardized value serves as the SPEI. For a detailed explanation
218 of this methodology can be found in Edwards and Mckee (1997).

219 The calculation of SPEI is performed using the R package "SPEI" ([https://cran.r-](https://cran.r-project.org/web/packages/SPEI)
220 [project.org/web/packages/SPEI](https://cran.r-project.org/web/packages/SPEI), last accessed on March 6, 2023). We use the log-logistic, and
221 unbiased probability weighted moments ('ub-pwm') for parameter estimation. The *PET* is
222 calculated using the FAO-56 Penman-Monteith method (Allen et al., 1998). Here, we calculate
223 the SPEI for different accumulation time scales, including 3 months (SPEI03, short-term), 6
224 months (SPEI06, mid-term), 12 months (SPEI12, mid-term), and 24 months (SPEI24, long-
225 term).

226 **2.3 Climate classification**

227 The latest Köppen-Geiger World map data (<http://www.gloh2o.org/koppen/>, last accessed 28
228 March 2023) is used in this analysis to classify the climate regime (Beck et al., 2018). This
229 classification was formulated by Wladimir Köppen and has undergone several updates over the
230 years (Peel et al., 2007; Kriticos et al., 2012). The most recent version was introduced by Beck
231 et al. (2018) and has an unprecedented resolution of 0.0083° (approximately 1 km at the
232 equator), which provides a more accurate representation of highly heterogeneous regions. To
233 ensure accuracy and assess uncertainties in map classifications, the authors combined climatic
234 air temperature and precipitation data from multiple independent sources, including
235 WorldClim V1 and V2 (Fick and Hijmans, 2017; Hijmans et al., 2005), Climatologies at High
236 resolution for the Earth's land Surface Areas (CHELSA) V1.2 (Karger et al., 2017), and
237 Climate Hazards Group's Precipitation Climatology (CHPclim) V1 (Funk et al., 2015). These
238 datasets have been explicitly corrected for topographic effects and, with the exception of the
239 CHELSA V1.2 temperature dataset, are based on a large number of stations ($\geq 34,542$ for
240 precipitation and $\geq 20,268$ for temperature). The use of multiple data sources allows for an
241 estimate of uncertainty in the derived classes. The resulting dataset defines 30 possible climate
242 types, which can be grouped into five main categories: tropical, dry, temperate, continental,
243 and polar regions (Figure S1 in Supplemental Material). For our subsequent analysis, we
244 employ the current climate Köppen-Geiger World map to delineate the five core climate zones.



245 This choice is based on its remarkable consistency across time scales (Yoo and Rohli, 2016).
246 Because of the Earth's tilted axis results in significant seasonal differences in solar radiation
247 between the northern and southern hemispheres. To provide a precise representation of the
248 seasonal impact of deforestation in these regions, we have classified them into Dry_n and
249 Dry_s, T_n and T_s, Polar_n and Polar_s, corresponding to dry, temperate, and polar regions
250 in the northern and southern hemispheres, respectively.

251 **2.4 Evaluation of the effect of forest on droughts**

252 The *deforest-global* experiment is a branch of the *piControl* experiment, sharing identical
253 parameters except for the land cover data. We can assess the climate response to land cover
254 change by contrasting the outcomes of these two experiments (Lawrence et al., 2016).
255 However, the SPEI is a Log-logistic distribution index, so we cannot simply subtract the indices
256 from the two experiments. For calculating changes in SPEI, we utilized datasets from the
257 *piControl* experiment as the reference period for each model and subsequently computed the
258 SPEI values. The last 30 years of the experiment (from year 51 to year 80) are considered the
259 stabilized period (Boysen et al., 2020; Luo et al., 2022). During this period, the effects of
260 deforestation have been fully expressed. Consequently, in this study, all analysis, excluding
261 time-series analysis, are carried out exclusively on data from this specified period. The
262 subsequent analysis is concentrated solely on land grids and SPEI changes in *deforest-global*
263 relative to *piControl* experiment. We utilize a two-tailed t-test to assess the significance of
264 changes in SPEI induced by deforestation.

265 In order to perform a time-series analysis, we use cubic spline regression approach to
266 obtain smooth curves that allow for effective analysis (Wood, 2017). This method involves
267 fitting unique cubic polynomials between each data point, resulting in a continuous and smooth
268 curve. These cubic splines enable the determination of rates of change and cumulative change
269 over a given interval. The "mgcv" function from the R package was used for this study
270 (<https://cran.r-project.org/web/packages/mgcv/mgcv.pdf>, last accessed on 6 March 2023).

271 **3. Results**

272 **3.1 Changes in deforestation and meteorological factors**

273 The *deforest-global* experiment focuses on removing trees from grid cells that were
274 predominantly covered by forests. Deforestation mainly occurs in selected areas of tropics,



275 temperate, and continental regions and the global pattern of deforestation is similar for all
276 models (Supplemental Material Figure S2). The multi-model ensemble mean (MME) results
277 reveal that the Amazon basin, Central Africa, eastern North America, and Europe experience
278 the most significant forest reductions. Large scale deforestation leads to an average global land
279 reduction in precipitation of $-10.15 \pm 4.91 \text{ mm yr}^{-1}$ (mean \pm standard deviation) from year 51
280 to year 80 (Figure S3). The tropical region experiences the most significant decrease in
281 precipitation ($-30.21 \pm 28.71 \text{ mm yr}^{-1}$), followed by the continental ($-13.07 \pm 7.04 \text{ mm yr}^{-1}$)
282 and temperate ($-11.60 \pm 15.78 \text{ mm yr}^{-1}$) regions, while the polar ($-5.42 \pm 4.46 \text{ mm yr}^{-1}$) and dry
283 ($-1.64 \pm 8.24 \text{ mm yr}^{-1}$) regions have the least decrease in precipitation (Table S3). Nevertheless,
284 the models show some differences in precipitation variability patterns (Figure S4). UKESM1-
285 0-L is the model with the most substantial decrease in precipitation (except in the dry region,
286 where GISS-E2-1-G shows the most reduction). BCC-CSM2-MR, CMCC-ESM2, and
287 MIROC-ES2L show increased precipitation following deforestation, whereas other models
288 indicate drier conditions.

289 For temperature, MME shows that deforestation leads to a global land cooling effect of
290 $-0.47 \pm 0.13 \text{ }^\circ\text{C}$ (Table S3). Notably, the continental region has experienced the most significant
291 cooling ($-1.07 \pm 0.25 \text{ }^\circ\text{C}$) despite not having the highest deforestation rate, while the tropical
292 region showed the least significant cooling ($-0.12 \pm 0.11 \text{ }^\circ\text{C}$). The dry and polar regions, which
293 have experienced less deforestation, also showed a cooling effect of $-0.32 \pm 0.09 \text{ }^\circ\text{C}$ and -0.32
294 $\pm 0.27 \text{ }^\circ\text{C}$, respectively. Overall, the results of the simulation demonstrate a clear cooling trend
295 globally and in four regions (excluding the tropical region) compared to the *piControl*
296 experiment (Figure S4). Likewise, the temperature response to forest change exhibits inter-
297 model variability in specific regions. For instance, in tropical areas, BCC-CSM2-MR, CMCC-
298 ESM2, and IPSL-CM6A-LR indicate a low-confidence cooling effect, while other models
299 simulate a warming effect (Figure S5). The substantial divergence in precipitation and
300 temperature response to forest change in models may arise from variations in parameterization,
301 particularly in the representation of phenology and evapotranspiration for different land cover
302 types (Pitman et al., 2009).

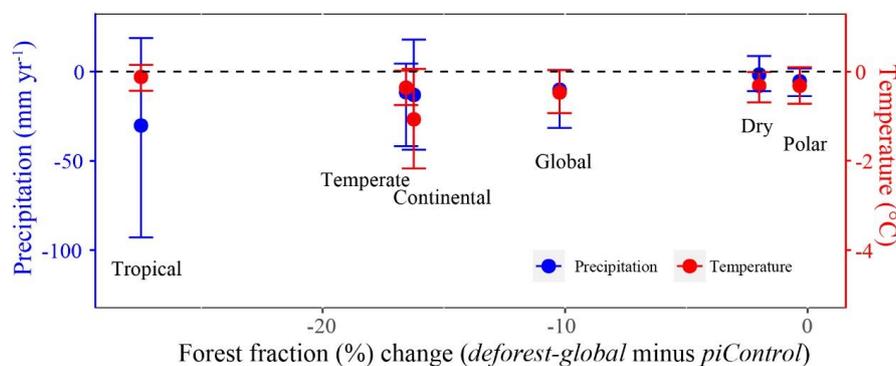
303 Table S3 displays the statistics regarding the average forest fraction, precipitation, and
304 temperature changes (*deforest-global* minus *piControl*) for each model individually over the
305 course of the analysis time period. Previous studies have shown a similar deforestation pattern
306 using *deforest-global* experiment datasets (Boysen et al., 2020; Lawrence et al., 2016), and
307 have demonstrated similar changes in global precipitation and temperature induced by global
308 deforestation (Boysen et al., 2020; Luo et al., 2022). Large-scale deforestation tends to reduce



309 land surface temperature predominately driven by altering albedo, especially at mid and high
 310 latitude combined with snow cover effect (Boysen et al., 2020; Perugini et al., 2017). It also
 311 reduces precipitation, primarily due to weakened evapotranspiration and atmospheric moisture
 312 convergence (Luo et al., 2022; Perugini et al., 2017). The inconsistent changes in deforestation
 313 and meteorological response patterns are likely due to the non-local biogeophysical impacts of
 314 deforestation (Winckler et al., 2019a; Badger and Dirmeyer, 2016).

315 Deforestation leads to a reduction in global precipitation and near-surface cooling, but
 316 the magnitude of these changes varies across regions and models (Figure 1). According to the
 317 different model outputs, some models estimate that the tropical region experiences the most
 318 significant decrease in precipitation and the least pronounced cooling. In contrast, the
 319 continental region typically experiences significant cooling, but the decrease in precipitation is
 320 less pronounced. In the temperate region, both precipitation and cooling changes are not very
 321 pronounced. The dry and polar regions, where fewer trees are removed, show slight variability
 322 in precipitation and temperature changes. Interestingly, there is no linear relationship between
 323 deforestation area and precipitation or temperature changes across regions, highlighting the
 324 complex and non-local nature of the biogeophysical effects of deforestation. Global and
 325 regional changes in forest fraction, precipitation, and near-surface temperature for individual
 326 models can be found in Figure S6.

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328

329 **Figure 1.** Global (only over land) and regional mean changes (*deforest-global* minus *piControl*) in forest
 330 fraction (%), precipitation (mm yr⁻¹), and near-surface temperature (°C). The dots represent the 30 years
 331 (from simulation year 51 to 80) average of multi-model ensemble mean results, and the vertical error bars
 332 represent the range of results from the nine models.

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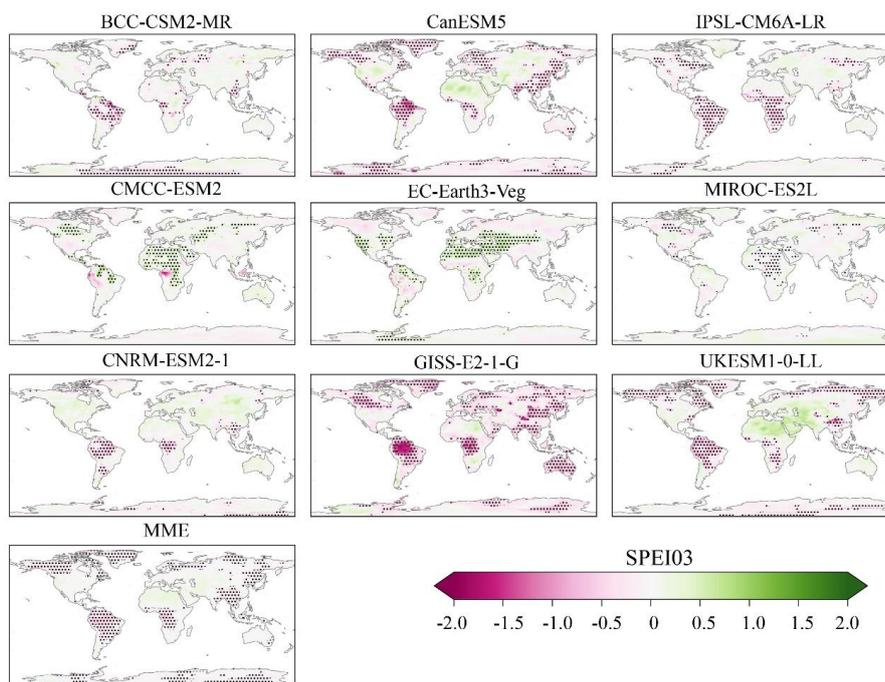
334 3.2 **Change in drought indices (SPEIs)**

335 3.2.1 **ANALYSIS OF ANNUAL AVERAGED CHANGES IN SPEIS**

336 For short-term drought (SPEI03), seven models indicate a tendency towards drier conditions
337 in the Amazon and tropical Africa. However, two models (CMCC-ESM2 and EC-Earth3-Veg)
338 show a significant wet trend in these regions (Figure 2). Most models simulate positive SPEI03
339 changes in North Africa, the Middle East, Central Asia, and Central North America, which are
340 classified as dry climate zones in global climate classification, suggesting an increase in
341 atmosphere moisture. Notably, the CMCC-ESM2 and EC-Earth3-Veg models show a
342 significant positive change in these areas. The MME also captures the drier Amazon and
343 tropical Africa, as well as the wetter conditions in dry climate zones.

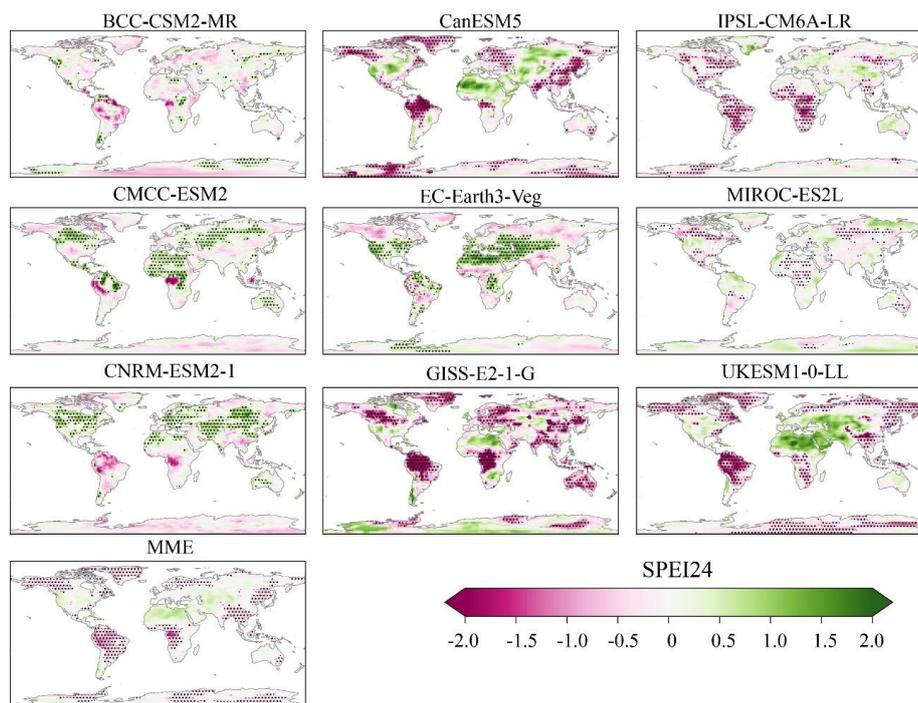
344 For long-term drought (SPEI24), models exhibit a similar pattern of changes in dry-wet
345 conditions as observed for short-term drought. Notably, significant changes in SPEI are evident
346 in the Amazon and tropical Africa across most models (Figure 3). In specific dry regions such
347 as North Africa, the Middle East, Central Asia, and Central North America, CMCC-ESM2,
348 EC-Earth3-Veg, and CNRM-ESM2-1 show a significant tendency towards wetter conditions,
349 while other models excluded GISS-E2-1-G indicate a slight wet trend that does not pass the
350 significance test. This highlights the influence of large-scale deforestation on local dry-wet
351 conditions, with some variability among models. The MME results demonstrate more
352 agreement with the majority of individual models in capturing the changes.

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355 **Figure 2.** Changes in the Standardized Precipitation-Evapotranspiration Index calculated over a 3-month
356 time scale (SPEI03) between the *deforest-global* and *piControl* experiment for nine GCMs and the Multi-
357 Model Ensemble mean (MME). Positive values signify increased moisture (wet conditions), while negative
358 values denote reduced moisture (dry conditions) relative to the *pi-Control* experiment. The black dots
359 indicate the changes in SPEI03, with significance tested using a two-tailed t-test at a p-value of 0.05.



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Fig. 3. Same as Fig.2 but for the SPEI calculated over a 24-month time scale (SPEI24).

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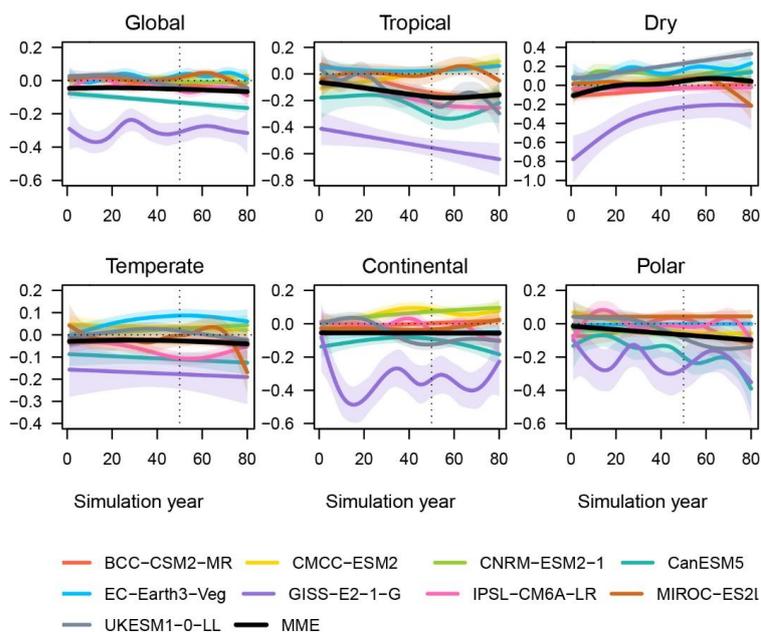
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The cubic spline regression analysis reveals that after the main forest is removed, the global mean short-term drought (SPEI03) shows a negative trend for the next 30 years (Figure 4), with an average value of -0.06 ± 0.02 (mean \pm standard deviation) during this period (Table S4). This negative trend remains relatively constant over the last 30 years. However, our findings show notable variations in the SPEI03 changes across different climate zones. In the tropical region, the SPEI03 time series indicates a significant decrease, with the rate of decline slowing down in the latter 30 years, resulting in a stable average value of -0.19 ± 0.04 (Table S4). And this region experiences the most significant dryness after deforestation. On the other hand, the dry region becomes more humid after global deforestation, with an average SPEI03 change of 0.07 ± 0.05 . The temperate, continental, and polar regions all experience negative changes in SPEI03, indicating varying degrees of desiccation. These findings underscore the crucial role of forests in regulating local and global climate patterns, especially in dry regions.



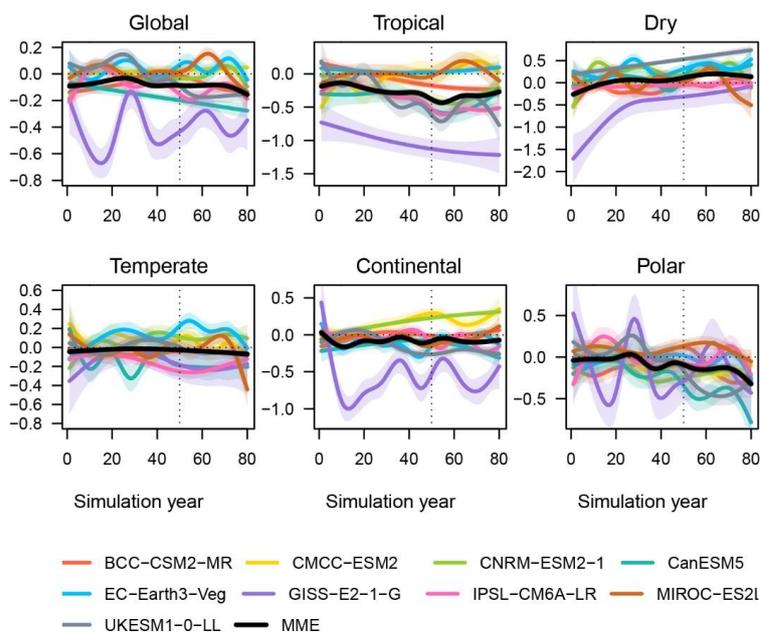
376

377 **Figure 4.** Global and regional annual averaged changes in SPEI03 due to deforestation are depicted over

378 time for each model and the MME. Different colors indicate different models. The solid lines denote cubic

379 spline regression, with significance indicated by shaded areas at a level of 0.05.

380

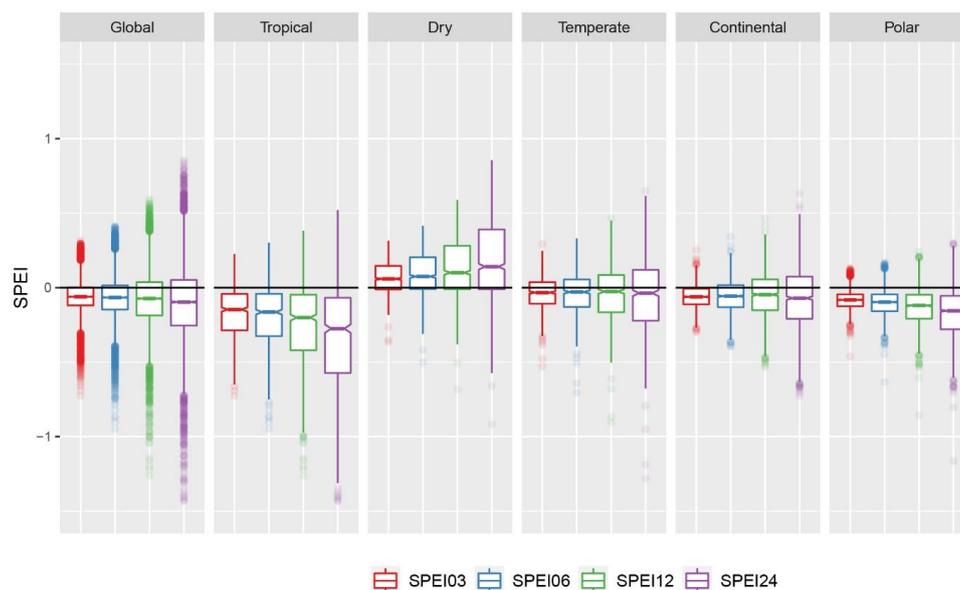


381

382 **Figure 5.** Same as Figure 4, but for the SPEI calculated over a 24-month time scale (SPEI24).

383

384 The impacts of deforestation on long-term drought (SPEI24) are more severe and have a
 385 large magnitude, and these changes are evident globally and regionally (Figure 5). However,
 386 there are differences in the simulation results among individual models. For instance, the GISS-
 387 E2-1-G model predicts the most severe droughts globally, in the tropics, dry, and continental
 388 regions, while the IPSL-CM6A-LR model produces the largest absolute average value for the
 389 latter 30 years in the temperate region. Additionally, the CanESM5 model shows that the polar
 390 region becomes drier after deforestation most clearly. These differences highlight the
 391 importance of considering multiple models when assessing the impacts of deforestation on
 392 droughts, as the specific outcomes may depend on the modelling approach used. The changes
 393 in spatial and temporal distribution for each individual model and the MME in mid-term
 394 drought can be observed in Figure S7 and S9 for SPEI06, while Figure S8 and S10 showcase
 395 the same for SPEI12.



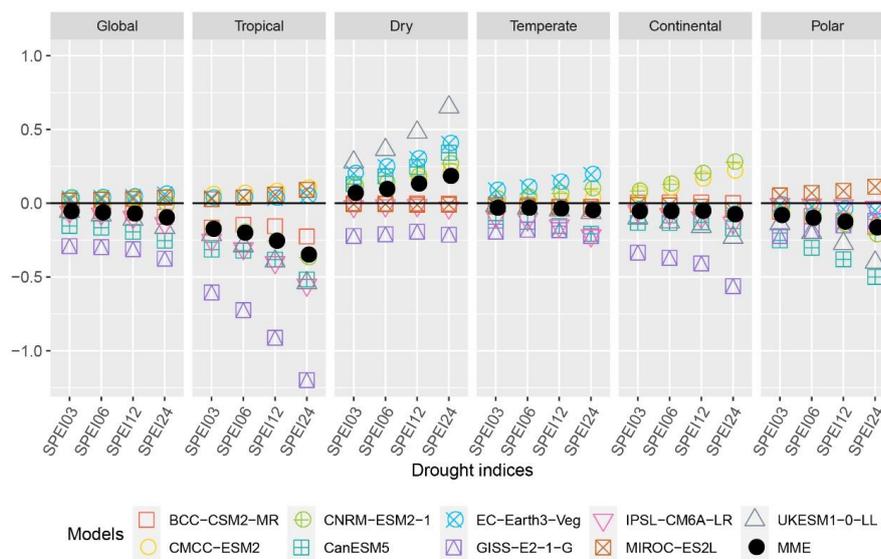
396

397 **Figure 6.** The box plots display the distribution of SPEIs (SPEI03, SPEI06, SPEI12, SPEI24) changes
 398 induced by deforestation averaged from year 51 to 80, globally and over the five climate regions for the
 399 MME. Each box plot represents the spatial variability of a specific SPEI, where the box represents the
 400 interquartile range (IQR) between the 25th and 75th percentiles, and the line inside the box represents the
 401 median. The whiskers extend to the minimum and maximum values within 1.5 times the IQR, and any data
 402 beyond the whiskers are shown as points. Different colors indicate different SPEIs.

403

404 We utilize box plots to offer a comprehensive perspective on the spatial variability of
 405 global and regional impacts resulting from deforestation on various SPEI indices for the MME
 406 (Figure 6). The analysis shows that large scale deforestation tends to lead to drier conditions,
 407 particularly noticeable in the context of long-term droughts. The tropical region is the most
 408 severely affected, followed by the dry, continental, and polar regions. In contrast, the temperate
 409 region seems to be the least affected, with a small mean value and large standard deviation
 410 (Table S4). For a specific model like GISS-E2-1-G, the most significant changes in drought
 411 indices due to large scale forest removal is observed, barring the polar region (Figure S11).
 412 Interestingly, in the polar areas, the CanESM5 model has the most substantial impact.
 413 Conversely, the MIROC-ES2L model demonstrates the slightest change, with a small value
 414 and large standard deviation. To our notice, the GISS-E2-1-G model indicates negative SPEI
 415 values in the dry region, which diverge from the results of other models.

416



417

418 **Figure 7.** The scatter plot shows the spatial and temporal averages (from year 51 to 80) of SPEIs (SPEI03,
 419 SPEI06, SPEI12, and SPEI24) across global and five climate regions for each model and the MME. Each
 420 model is represented by a different colored marker, while the MME averages are represented by the black
 421 solid circles.

422

423 Large-scale deforestation induces a global mean negative change in SPEIs, indicating
 424 increased global aridity post-deforestation (Figure 7). Among the five climate regions, tropical
 425 and arid areas appear most susceptible to deforestation. Deforestation within the tropical belt
 426 results in a negative SPEI change, signaling heightened aridity in the region. Conversely,
 427 deforestation in arid zones yields a positive SPEI change, indicative of increased moisture.
 428 Despite its lower deforestation rate (Table S3), the polar region displays a more substantial
 429 SPEI change compared to the continental and temperate regions (ranking second and third,
 430 respectively, in deforestation within the deforest-global experiment). These findings suggest
 431 that deforestation's impact extends to global climates, especially in regions with relatively
 432 uniform ecological compositions, such as arid and polar zones. As the time scale increases, the
 433 impact of global forest removal on the drought conditions becomes more pronounced,
 434 suggesting a greater influence on long-term drought conditions compared to the pre-industrial
 435 forest cover (Figure 7).

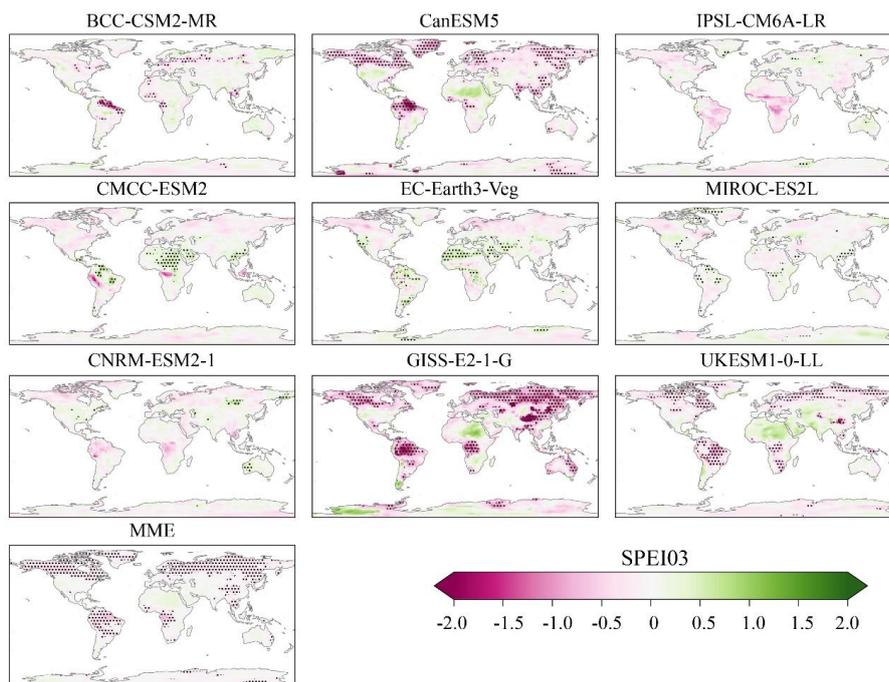
436 **3.2.2 ANALYSIS OF AVERAGED SEASONAL CHANGES IN SPEI03**



437 The high-latitude region in northern North America, northern Europe (excluding Greenland),
438 and northern Asia experience more pronounced seasonal changes in SPEI03 following
439 deforestation (Figure 8 and 9). Specifically, these regions become drier in December-January-
440 February (DJF, Figure 8) and wetter in June-July-August (JJA, Figure 9). In contrast, there is
441 no clear seasonal pattern in the SPEI03 variation in the middle and low latitudes, with some
442 variation depending on the latitude. We also observe that SPEI03 becomes negative in the
443 tropical region after deforestation, while in the dry region in the northern hemisphere, it
444 becomes positive, with no significant seasonal variation. Additionally, Supplemental Material
445 Figures S12 and S13 show the March-April-May (MAM) and September-October-November
446 (SON) changes resulting from deforestation during the same period. Overall, our results
447 suggest that deforestation has a significant impact on the seasonal variability of short-term
448 drought, especially in high-latitude regions.

449 The simulation results in the effect of deforestation on SPEI03 exhibit model variations,
450 with some models unable to capture the seasonal changes in drought induced by deforestation
451 as seen in the MME. The IPSL-CM6A-LR model, for example, shows no significant difference
452 in SPEI03 variation between DJF and JJA. Furthermore, simulation results for certain regions
453 in Asia and Europe's high latitudes indicate the opposite result to the MME, with a wetter
454 winter and drier summer. It is worth noting that the regions with the most significant seasonal
455 fluctuations in SPEI03 are mainly located in the continental zone. Therefore, a deeper analysis
456 of the seasonal impact of deforestation on drought in this region is needed.

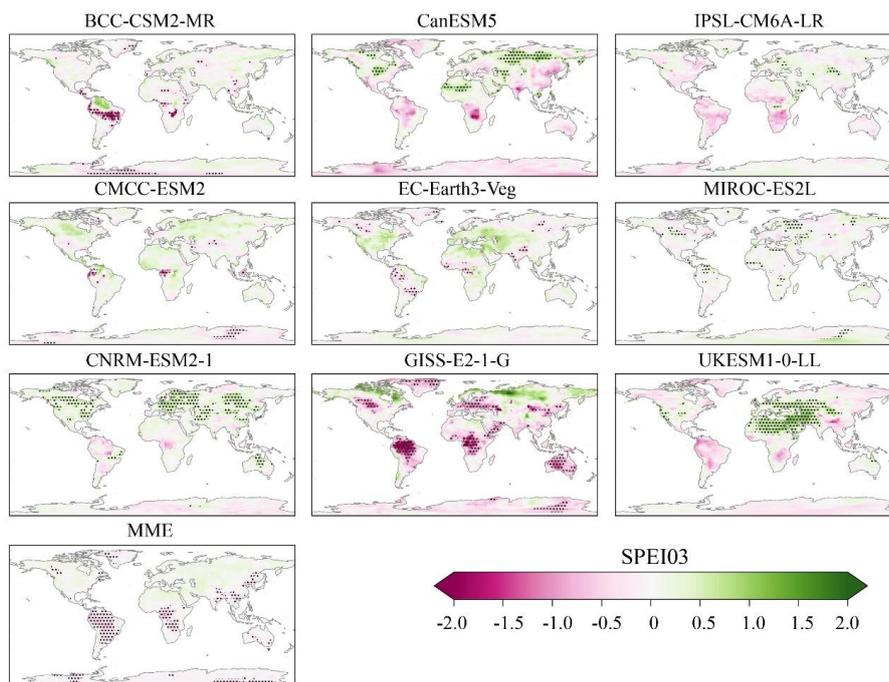
457



458

459 **Figure 8.** Changes in the Standardized Precipitation-Evapotranspiration Index calculated over a 3-month
460 time scale (SPEI03) during December-January-February (DJF) between the *deforest-global* and *piControl*
461 experiment for nine GCMs and the Multi-Model Ensemble mean (MME). Positive values signify increased
462 moisture (wet conditions), while negative values denote reduced moisture (dry conditions) relative to the *pi-*
463 *Control* experiment. The black dots indicate the changes in SPEI03, with significance tested using a two-
464 tailed t-test at a p-value of 0.05.

465



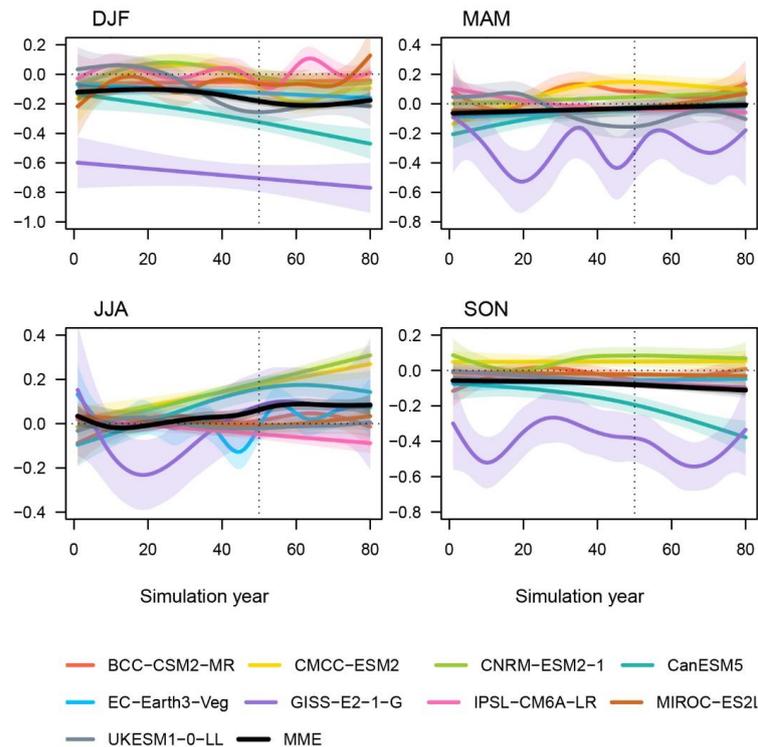
466

467 **Figure 9.** Same as Figure 8, but during June-July-August (JJA).

468

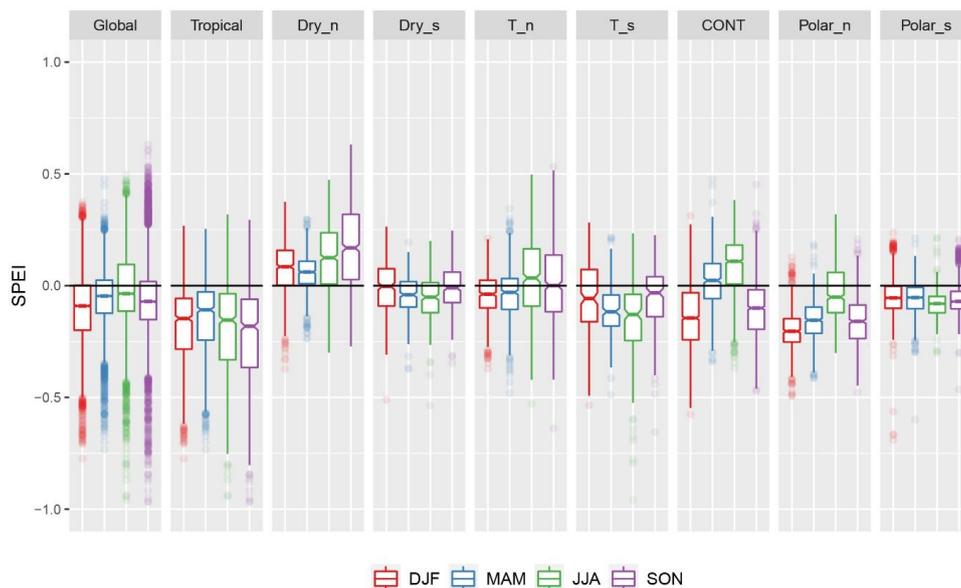
469 Deforestation impact on continental drought is most significant during DJF and JJA, with
 470 a smaller effect during MAM and SON (Figure 10). The MME results show negative values
 471 for winter SPEI03 time series changes, with an average of -0.20 ± 0.07 . Most models, except
 472 for IPSL-CM6A-LR (with an average of 0.00 ± 0.14), can capture the characteristics of a drier
 473 condition tendency in DJF. Similarly, in the northern hemisphere summer (JJA), MME and
 474 most models (except IPSL-CM6A-LR, with an average of -0.06 ± 0.11) indicate positive values.
 475 However, in the MAM and SON seasons, the model outputs display a blend of both positive
 476 and negative values. In contrast, the MME results are predominantly negative, although to a
 477 lesser extent compared to the winter season. More details about the seasonal changes of SPEI03
 478 in different regions are available in Supplemental Material Figure S14-S18.

479



480

481 **Figure 10.** Seasonal changes in SPEI03 induced by deforestation averaged in the continental region for each
482 model and the MME. Each model is represented by a different color. The solid lines denote cubic spline
483 regression, with significance indicated by shaded areas at a level of 0.05.



484

485 **Figure 11.** Box plots represent the seasonal (DJF, MAM, JJA, SON) changes in SPEI03 across different
 486 areas (global and eight regions) for the MME. Each box shows the interquartile range (IQR) of the SPEI03
 487 changes within a specific region, with the lower and upper edges corresponding to the 25th (Q1) and 75th
 488 (Q3) percentiles, respectively. Outliers are also displayed and defined as values less than $Q1-1.5 \times (IQR)$ or
 489 greater than $Q3+1.5 \times (IQR)$. Different colors are used to represent different seasons.

490

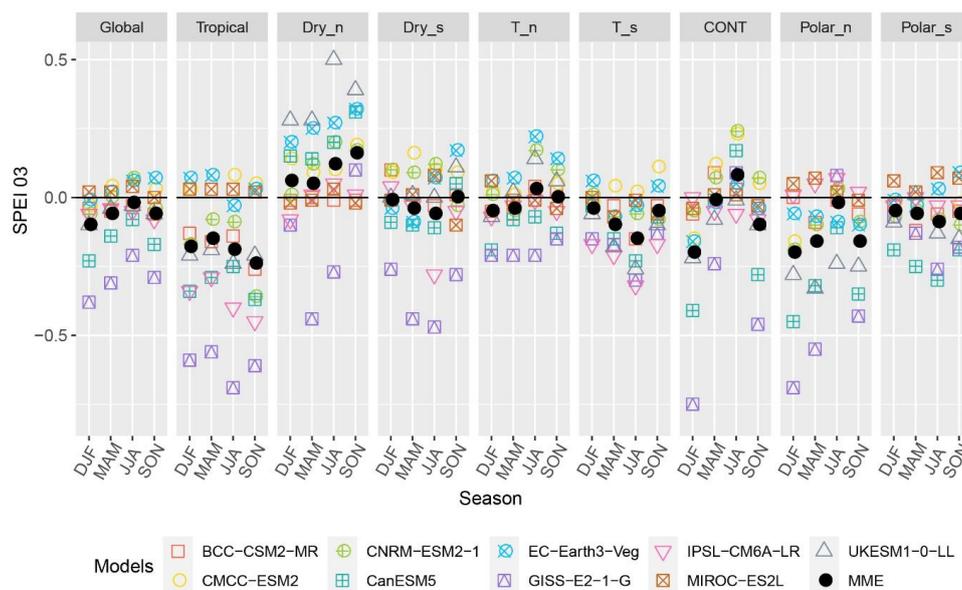
491 Figure 11 highlights the impact of deforestation on SPEI03 across different regions and
 492 seasons. The MME results reveal that deforestation leads to a negative effect on SPEI03 in all
 493 seasons, with the most substantial impact observed in the northern hemisphere's winter half-
 494 year (SON and DJF). In the tropical region, deforestation significantly decreases SPEI03 in all
 495 seasons. Conversely, the Dry_n region experiences a positive change in SPEI03 following
 496 deforestation, indicating a wetter climate, with the effect being more pronounced in summer
 497 and autumn. The Dry_s region, however, does not exhibit any significant change in SPEI03.
 498 Notably, the continental region experiences the most significant seasonal change in SPEI03
 499 following deforestation, with a considerable decrease in the northern hemisphere's winter and
 500 a marked increase in northern hemisphere's summer, indicating that the impact of deforestation
 501 differs between the two seasons. These results underscore the region-specific nature of the
 502 impact of deforestation on drought, and understanding the seasonal patterns of these changes
 503 is crucial for developing effective mitigation and adaptation strategies.



504 The box plots depict the variability in SPEI03 seasonal changes observed among different
505 regions and models (Figure S19). The global region, for instance, presents diverse trends in
506 SPEI03 changes across models. Specifically, while five models (BCC-CSM2-MR, CanESM5,
507 GISS-E2-1-G, IPSL-CM6A-LR, UKESM1-0-LL) indicate an overall decrease in SPEI03 for
508 four seasons, one model (MIROC-ES2L) shows an overall increase in SPEI03 for four seasons,
509 and it suggests that deforestation leads to positive changes in SPEI03 for the tropical and
510 Polar_n regions, which contradicts the conclusions of most models. These results highlight the
511 need to account for the variability across multiple models when interpreting the findings of this
512 study. It is essential to exercise caution when drawing conclusions based on the results of any
513 individual model and consider a more comprehensive approach that accounts for the variability
514 across multiple models.

515 There is a clear distinction among the models in illustrating the global and regional
516 averaged SPEI03 shifts following deforestation (Figure 12). Overall, the results show that
517 deforestation leads to a negative shift in average SPEI03 values globally, indicating a drier
518 climate, particularly during the north hemisphere winter and autumn. This trend is consistent
519 in the tropical and northern hemisphere polar regions as well. In the continental region,
520 however, the average changes of SPEI03 are negative during DJF and positive during JJA,
521 showing an opposing trend. These findings are in line with the box plots presented in Fig. 11.
522 Furthermore, the comparison among the nine models shows that the GISS-E2-1-G model is
523 more sensitive to the seasonal effects of deforestation on drought, with results mostly spread
524 in the lower part of the figure (except for the polar region, where CanESM5 shows the most
525 fluctuation in SPEI03). Conversely, the majority of SPEI03 outcomes for the EC-Earth3-Veg
526 and CNRM-ESM2-1 models are positive, suggesting that the world will become wetter
527 following deforestation.

528



529

530 **Figure 12.** The scatter plot shows the global and climate regional averaged changes of SPEI03 induced by
 531 deforestation for each season and model, as well as the multi-model ensemble (MME). Each colored marker
 532 represents a different model.

533

534 In general, the global averaged SPEI03 shifts are more prominent in the boreal autumn
 535 and winter seasons following deforestation, which is also observed in both tropical and
 536 northern hemisphere polar regions. The temperate zone is the least affected by deforestation.
 537 Moreover, the continental region experiences the most seasonal change, with a negative
 538 SPEI03 (drier) in winter and a positive SPEI03 (wetter) in summer. In line with the previous
 539 analysis of annual variability, the northern hemisphere dry region is the only area that becomes
 540 wetter following deforestation, and this is most noticeable in the autumn season.

541 4. Discussion

542 In this study, we use idealized deforestation experiments (*deforest-global*) and pre-industrial
 543 control simulation experiments (*piControl*) conducted by nine global climate models from
 544 LUMIP dataset bank to examine the impacts of global deforestation on droughts across
 545 different climate regions and time scales. Deforestation has been consistently shown by various
 546 model simulations to lead to a decrease in global precipitation, with the tropical region
 547 experiencing the most significant reduction. This concurs with the observed decrease in



548 precipitation change attributed to forest loss in tropical regions (Smith et al., 2023). Moreover,
549 it is expected to cause cooling, particularly in the continental region. Similar findings have
550 been reported in previous studies (Boysen et al., 2020; Cherubini et al., 2018; Perugini et al.,
551 2017). Biogeophysical mechanisms such as changes in evapotranspiration and atmospheric
552 moisture convergence play a crucial role in causing changes in precipitation (Zhang et al.,
553 2021), while reduced available energy is primarily responsible for temperature changes (Luo
554 et al., 2022). The effects of deforestation on the climate vary depending on the location, with
555 boreal deforestation primarily increasing albedo and tropical deforestation mainly decreasing
556 evapotranspiration (Chen and Dirmeyer, 2020; Spracklen et al., 2012; Winckler et al., 2019b).

557 Large-scale deforestation can significantly increase the risk of global droughts, as
558 droughts are influenced by various factors such as precipitation, temperature, and other
559 biogeophysical factors. Deforestation has contrasting effects on cloud cover across different
560 regions: it typically decreases cloud cover in tropical areas while increasing it in dry, temperate,
561 and continental regions (Figure S20). This reduction in cloud cover in the tropics is primarily
562 attributed to a decrease in local cloud formation, whereas there is a non-local enhancement of
563 cloud cover in temperate and boreal regions (Duveiller et al., 2021; Hua et al., 2023). The
564 changes in cloud cover induced by deforestation are predominantly driven by sensible heating,
565 with areas of higher sensible heat more likely to experience cloud enhancement, while areas
566 with lower sensible heat tend to see cloud inhibition over forests (Xu et al., 2022). These
567 alterations in cloud cover subsequently influence incoming surface radiation. Meanwhile, the
568 changes of forests also impact on the surface albedo, and then the flux exchange between land
569 surface and atmosphere, which in turn impacts surface potential evapotranspiration.
570 Specifically, deforestation tends to increase potential evapotranspiration in tropical regions
571 while decreasing it in middle-to-high latitudes, particularly in dry regions (Figure S21). Despite
572 these changes, large-scale deforestation typically results in more precipitation in dry regions
573 and less precipitation in tropical regions (Figure S3 and S6). In tropical regions, deforestation
574 leads to a significant reduction in transpiration, which disrupts water recycling processes and
575 contributes to lower precipitation levels, exacerbating dry conditions (Staal et al., 2020; Staal
576 et al., 2018; Van Der Ent et al., 2014). Conversely, in dry regions, the increase in precipitation
577 and decrease in potential evapotranspiration induced by deforestation often result in wetter
578 conditions. Li et al. (2024) also confirmed that precipitation is the primary factor affecting
579 droughts in the tropical region, while temperature is the primary factor affecting droughts in
580 the dry region. The dry region experiences precipitation deficits and cooling effects after the
581 removal of trees, and the cooling effect could contribute to increased moisture, so global



582 deforestation can potentially mitigate droughts in this region, showcasing the non-local impact
583 of deforestation. In contrast, the temperate and continental regions are the most stable in terms
584 of droughts following deforestation.

585 Our study also focuses on analyzing the effects of an idealized deforestation scenario on
586 seasonal changes in SPEI03, and found that the continental zone is most affected through
587 variations in drought. The insights into the possible reasons behind this phenomenon is that
588 deforestation in the continental region has contrasting effects on temperature, causing cooling
589 in winter and spring but warming in summer, as previously reported in other studies (Alkama
590 and Cescatti, 2016; Cherubini et al., 2018). Deforestation increases surface albedo in winter by
591 removing tree cover, which leads to a decrease in the net radiation balance and surface
592 temperature. Conversely, in summer, the reduced evapotranspiration and surface roughness are
593 the primary causes of temperature increases. Additionally, using the CCM3-IBIS coupled
594 atmosphere-biosphere model, Snyder et al. (2004) demonstrated that deforestation leads to a
595 substantial reduction in precipitation in summer (-0.7 mm day^{-1}) and the least reduction in
596 winter (-0.2 mm day^{-1}) in the continental region. Removing trees leads to a significant reduction
597 in transpiration, which is particularly pronounced during summer and to a smaller extent in
598 winter (Cai et al., 2019). This reduction may contribute to a situation where there is a greater
599 conflict between reduced precipitation and transpiration during winter compared to summer,
600 and then leads to a drier winter in the continental region. Therefore, we conclude that the
601 combined biogeophysical effects of deforestation in the continental region could explain the
602 wetting effect in summer and the drying effect in winter.

603 We investigate the influence of global deforestation on regional drought patterns within
604 the five main climate zones as classified by the Köppen-Geiger system. However, it is
605 important to acknowledge that our analysis does not account for sub-climates within these
606 zones. Instead, we focus on determining the average changes in drought for each climate zone,
607 providing a broader assessment. Among the climate zones studied, the dry climate zone,
608 encompassing steppe and desert climates and representing approximately 26% of the Earth's
609 land area, exhibited heightened vulnerability to changes in drought patterns. Interestingly, our
610 findings indicate that this region is likely to experience reduced drought occurrences following
611 forest removal, primarily due to the non-local effects associated with global deforestation. It is
612 worth noting that the degree of forest replacement with grass was relatively lower within the
613 dry climate zone in our study. To obtain more precise and specific conclusions, it is advisable
614 to further subdivide the climate divisions, enabling a more nuanced analysis. This approach
615 would enhance the accuracy and granularity of our findings, particularly when examining the



616 response of different sub-climates within each climate zone to deforestation-induced changes
617 in drought. Furthermore, our study utilizes models with relatively coarse spatial resolutions,
618 ranging from $0.7^{\circ} \times 0.7^{\circ}$ to $2.8^{\circ} \times 2.8^{\circ}$, depending on the specific model employed. This coarse
619 resolution may have resulted in some loss of information, particularly when investigating
620 regional variations in drought. To address this limitation, future studies could employ higher-
621 resolution models, which would provide a more accurate understanding of how land use
622 changes impact regional drought patterns. For instance, the integration of data from projects
623 such as the Land Use and Climate Across Scales Flagship Pilot Study (LUCAS FPS) could
624 significantly enhance our investigations. LUCAS FPS utilizes regional climate models to
625 quantify the biogeophysical effects of land cover change in specific regions, such as Europe
626 (Davin et al., 2020). Incorporating regional climate models and higher-resolution data would
627 enable a more comprehensive examination of the intricate relationship between land use
628 changes and drought patterns at the regional level.

629 Recent observations indicate that changes in dry spells across northeastern South
630 America and the West Africa/Sahel region are primarily influenced by anthropogenic factors
631 (Wainwright et al., 2022). Specifically, the lengthening trend of dry spells in South America is
632 likely linked to deforestation, altering moisture recycling and reducing latent heat flux (Leite
633 et al., 2019). Changes in forest cover, predominantly due to restoration of forest from cropland,
634 have significant local climatic impacts in Europe (Huang et al., 2020). Model simulations
635 reveal that deforestation induces a cooler and drier climate in Europe (Hu et al., 2019;
636 Cherubini et al., 2018). Furthermore, alterations in forests, including activities like forest
637 harvesting, modify various surface attributes such as leaf area index and canopy structure,
638 consequently affecting surface roughness, energy transfer, and solar radiation absorption
639 (Huang et al., 2023; Anderson et al., 2011). These surface disturbances can potentially
640 influence the general circulation of the atmosphere (Badger and Dirmeyer, 2016). However,
641 the extent to which modifications in the general circulation, propelled by changes in forests
642 and their influence on inter-hemispheric heating, particularly impacting the position of the
643 intertropical convergence zone (Frierson et al., 2013; Stephens et al., 2022) and the movement
644 of rainfall belts (Frierson et al., 2013; Dong and Sutton, 2015), remains largely unknown.

645 This analysis shows a diverse climate response (temperature, precipitation, and SPEIs)
646 resulting from large-scale forest losses. Although these models share a common framework by
647 deforesting the top 30% grid cells relative to their forested fraction in the *piControl* land cover
648 (Lawrence et al., 2016), there are variations in defining forest fractions within the *piControl*
649 stage across models. For instance, the IPSL-CM6A-LR model utilizes the ORCHIDEE land



650 surface model, representing vegetation heterogeneity with 15 plant functional types (Boucher
651 et al., 2020), while the CNRM-ESM2-1 model, coupled with the ISBA-CTRIP land surface
652 model, incorporates 16 vegetation types (Decharme et al., 2019; Delire et al., 2020).
653 Differences in the spatial pattern of deforestation among models predominantly stem from
654 variations in initial forest cover, ranging from 36 to 66 Mkm² (Boysen et al., 2020). This
655 disparity underscores the challenges in implementing consistent land use and cover change
656 scenario (Di Vittorio et al., 2014). Moreover, these models employ distinct land surface models
657 with varying approaches to vegetation phenology and carbon cycle, further influencing the
658 climate response to deforestation (Boysen et al., 2020). For example, the terrestrial
659 biogeochemical processes in CMCC-ESM2 are represented by the Community Land Model
660 version 4.5 (CLM4.5) in its biogeochemical configuration including key processes concerning
661 global carbon and nitrogen cycles (Oleson et al., 2013; Koven et al., 2013). Photosynthesis
662 descriptions vary among plant types, with C3 plants (Farquhar et al., 1980) and C4 plants
663 (Collatz et al., 1992). These methods differ in leaf-level parameterization of carboxylation and
664 limiting factors. The resulting photosynthate is allocated into various vegetation carbon pools,
665 and the transfer of carbon into litter-soil pools follows a dynamic cascade (Parton et al., 1988).
666 EC-Earth-veg employs LPJ-GUESS land surface model to simulate vegetation dynamics,
667 management, land use, terrestrial carbon and nitrogen cycles, and incorporating six stand-types
668 (Natural, Pasture, Urban, Crop, Irrigated Crop, and Peatland). LPJ-GUESS features
669 competition among plant functional types within each stand-type, with tree establishment
670 disabled on deforested areas, leaving only herbaceous PFTs in competition. The model
671 represents global carbon and nitrogen cycles within vegetation, litter, and soil organic matter
672 pools, influencing soil biogeochemistry, CO₂ fluxes, and nitrogen trace gas emissions. The
673 distinct variations in vegetation phenology across models will also influence aerodynamic
674 resistance following forest replacement, thereby significantly contributing to changes in
675 surface temperature (Liu et al., 2023). These temperature changes can subsequently impact
676 potential evapotranspiration and, consequently, drought conditions. Considering the wide-
677 ranging initial forest cover and the distinct land surface models used, it becomes evident that a
678 comprehensive approach involving multi-model simulations is crucial. Such an approach
679 allows for a more comprehensive understanding of the relative realistic climate effects resulting
680 from large-scale deforestation.

681 As human societies continue to rapidly develop, it is increasingly important to understand
682 the impacts of land use changes on both climate and humans. This study utilizes data from nine
683 models to analyze the responses of droughts at different time scales and across various climate



684 zones to deforestation. However, some uncertainties remain in this research. Firstly, while the
685 models all follow the same experimental setup, the extent and location of deforestation varies,
686 which may lead to different climate responses. Secondly, the drought index used in this study,
687 SPEI, primarily considers atmospheric conditions and overlooks the effects of soil drought.
688 Finally, this study only scratches the surface of the calculated drought indices, and additional
689 statistical models should be employed to explore the impacts of deforestation on drought across
690 different time scales and climate zones. Future research can address these gaps and further
691 investigate the development of natural hazards.

692 In this paper, we focus on the combined effects of local and non-local effects of
693 deforestation, and in the future, we can further analyze the different responses (local and non-
694 local) to deforestation and the weight of the different responses in each region. Here, we have
695 only analyzed the effect of deforestation on the magnitude of the drought, but we can also
696 analyze the effect on the onset, termination and duration of the drought. Additionally, future
697 research also could consider incorporating other factors that may influence the response of
698 drought to deforestation, such as soil characteristics, topography, and vegetation type.
699 Furthermore, it would be interesting to investigate the potential feedback mechanisms between
700 the changes in climate and the resulting changes in vegetation cover, as well as the impacts of
701 deforestation on other hydrological processes, such as runoff and groundwater recharge. Lastly,
702 further research can be conducted to assess the economic and social impacts of deforestation-
703 induced drought and to explore potential mitigation and adaptation strategies for vulnerable
704 regions.

705 5. Conclusions

706 This study extensively investigates the impact of deforestation on droughts at various time
707 scales (SPEI03, SPEI06, SPEI12, SPEI24) across different climate regions (tropical, dry,
708 temperate, continental, and polar regions). We accomplish this by utilizing simulations from
709 nine models in the pre-industrial control simulation (*piControl*) of CMIP6 and the LUMIP
710 global deforestation experiment (*deforest-global*). Based on our analysis of the results, we draw
711 conclusions about the effects of deforestation on droughts in different climate regions.

712 1. The LUMIP global deforestation experiment was conducted with the same framework
713 requirements. Deforestation primarily occurred in tropical, temperate, and continental regions.
714 This is because the experimental setup involved deforestation in the grid where the forest area
715 was among the top 30% largest, meaning that the most heavily forested areas were selected for



716 deforestation. The results of the experiment indicate that deforestation on a global scale can
717 significantly alter precipitation and temperature patterns. Tree removal caused a considerable
718 reduction in temperature over the land, particularly in the continental regions, while also
719 resulting in a decrease in global and regional precipitation. The tropical regions are the most
720 affected by this reduction in precipitation.

721 2. The analysis reveals that deforestation leads to negative changes in the global average
722 of SPEIs, resulting in drier conditions. This trend is most pronounced in the tropical region.
723 However, in the dry region, deforestation results in increased SPEIs. In the temperate and
724 continental regions, which are major global forest belts, deforestation has a relatively limited
725 impact. Moreover, our findings indicate that the effect of deforestation on drought indices
726 increases with longer time scales, suggesting that deforestation has a more significant impact
727 on the long-term drought index.

728 3. At the seasonal scale, global average SPEI03 changes are more significant in autumn
729 and winter following deforestation. This trend is also detected in tropical and northern polar
730 regions, while the northern hemisphere temperate zone is the least affected. The continental
731 region experiences the most significant seasonal changes, becoming drier in winter and wetter
732 in summer due to global deforestation. In the dry northern hemisphere region, deforestation
733 leads to increased atmospheric moisture, which is most evident in autumn.

734 In summary, this study provides valuable insights into the impact of large-scale
735 deforestation on global and regional droughts across different time scales, which serves as a
736 starting point for further exploration of the complex relationships between land cover change
737 and climate. Overall, our study could inform the development of climate-oriented land use
738 policies and increase our understanding of the regional and global climate impacts of land cover
739 change. Further research in this field could ultimately help us to mitigate the negative effects
740 of land use change on the environment and society.

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743 *Acknowledgments.*

744 YL gratefully acknowledges the support provided by the China Scholarship Council (CSC).
745 BH and FC extend their appreciation for the support received from the Norwegian Research
746 Council (project no. 286773 and 294534). CT thanks the support of the National Natural
747 Science Foundation of China (Grant No. 42201085) and the Regional Innovation Cooperation
748 Project of the Science & Technology Department of Sichuan Province (Grant No.



749 2023YFQ0105). The authors would also like to extend their appreciation to the CMIP6 LUMIP
750 modeling group and ESGF for providing access to the available CMIP6 data.

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752 *Code/Data Availability Statement.*

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754 The simulations of the CMIP6 *piControl* experiment and the LUMIP *deforest-globe*
755 experiment are available at <https://esgf-node.llnl.gov/search/cmip6/>.

756

757 *Author contribution*

758 The research was conceptualized and designed by YL, BH, and HWR. BH was responsible
759 for downloading and initially processing the data. YL and BH conducted data analysis and
760 generated the figures. YL drafted the initial version of the paper. All authors participated in
761 result interpretation and contributed to writing the final paper.

762

763 *Competing interests*

764 The contact author has declared that none of the authors has any competing interests.

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