

ACCEPTED MANUSCRIPT • OPEN ACCESS

Neglecting plant physiology: systematic overestimation of drought projections

To cite this article before publication: Lorenzo Villani *et al* 2026 *Environ. Res.: Climate* in press <https://doi.org/10.1088/2752-5295/ae583c>

Manuscript version: Accepted Manuscript

Accepted Manuscript is “the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an ‘Accepted Manuscript’ watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors”

This Accepted Manuscript is © 2026 The Author(s). Published by IOP Publishing Ltd.



As the Version of Record of this article is going to be / has been published on a gold open access basis under a CC BY 4.0 licence, this Accepted Manuscript is available for reuse under a CC BY 4.0 licence immediately.

Everyone is permitted to use all or part of the original content in this article, provided that they adhere to all the terms of the licence <https://creativecommons.org/licenses/by/4.0>

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions may be required. All third party content is fully copyright protected and is not published on a gold open access basis under a CC BY licence, unless that is specifically stated in the figure caption in the Version of Record.

View the [article online](#) for updates and enhancements.

Journal Title

TOPICAL REVIEW

Neglecting Plant Physiology: Systematic Overestimation of Drought Projections

Lorenzo Villani^{1*}, Luigi Piemontese¹, Giulio Castelli¹, Andrea Borgo^{2,3}, Nicolas Ghilain^{4,5}, Bert Van Schaeybroeck⁵, Enrico Lucca¹, Muhammad Faizan Aslam^{2,3}, Marta Debolini³, Ismail Bouizrou^{1,6}, Estifanos Addisu Yimer⁷, Miriam Baudewyn⁴, Fernando Jaramillo⁸, Antonio Trabucco³, Ann van Griensven^{7,9}, Daniele Penna^{1,10} and Elena Bresci¹.

¹ Department of Agriculture, Food, Environment and Forestry (DAGRI), Università degli Studi di Firenze, Italy
² Department of Agriculture, University of Sassari, Viale Italia, 39a, 07100 Sassari, Italy
³ CMCC Foundation – Euro-Mediterranean Centre on Climate Change, Italy
⁴ Department of Geography, University of Liege, Liege, Belgium
⁵ Meteorological and Climatological Research Unit, Royal Meteorological Institute of Belgium, Brussels, Belgium
⁶ Institute of Ecology and Landscape, Hochschule Weihenstephan-Triesdorf University (HSWT), Freising, Germany
⁷ Department of Water and Climate, Vrije Universiteit Brussel, 1050 Brussels, Belgium
⁸ Department of Physical Geography/Bolin Centre for Climate Research, Stockholm University, Stockholm, Sweden
⁹ Department of Water Science and Engineering, IHE Delft Institute for Water Education, 2700 Delft, the Netherlands
¹⁰ Forest Engineering Resources and Management Department, Oregon State University, Corvallis, USA
*Author to whom any correspondence should be addressed.

E-mail: lorenzo.villani@unifi.it

Keywords: Plant physiological response, atmospheric evaporative demand, potential evapotranspiration, CO₂ fertilization effect, stomatal resistance, Standardized Precipitation Evapotranspiration Index, Palmer Drought Severity Index.

Abstract

The impact of climate change on droughts is typically attributed to rising temperatures and altered precipitation patterns. Yet, most drought projections overlook a major climate-induced mechanism: the effect of elevated CO₂ on plant physiology, leading to a significant potential overestimation of droughts magnitudes and impacts. In fact, elevated CO₂ enhances biomass production and reduces stomatal conductance, thereby increasing water-use efficiency . Our systematic review reveals that nearly 90% of evapotranspiration-based drought projections omit CO₂-driven vegetation feedback, and only 10% acknowledge this limitation. Neglecting vegetation response to CO₂ can overestimate future drought-affected areas by up to 17.4 ± 10.6% under high-emission scenarios (CO₂ > 900 ppm), and in some regions even reverse the projected direction of change. This widespread oversight can hamper the robustness of global drought projections. Accounting for vegetation–CO₂ interactions is therefore crucial to avoid systematic bias and produce reliable predictions of water availability in a warming world.

1. Introduction: The misalignment between offline drought projections and climate model outputs

Droughts are extremely complex hazards with subtle, indirect and delayed impacts on multiple sectors (Hagenlocher et al., 2023; Van Loon et al., 2016a, b). To delve into this complexity, scholars typically divide drought into meteorological, agricultural, hydrological and socioeconomic drought (Mishra and Singh, 2010). As a result, a plethora of indices are available to estimate drought characteristics based on multiple climatological or hydrological variables (Damkjaer & Taylor, 2017; Kchouk et al., 2022). By far, the most considered flux in the hydrological cycle is precipitation, and the most-applied drought index is the Standardized Precipitation Index (SPI) (McKee et al., 1993; Kchouk et al., 2022). Nevertheless, with the increased availability and accessibility of data, also due to the emergence of remote sensing and re-analysis products, dozens of indices have been proposed which include variables other than precipitation (Han and Singh, 2023; Zargar et al., 2011). The atmospheric evaporative demand (AED), also referred to as reference (ET_r; DeJonge et al., 2025) or potential evapotranspiration (PET¹; Brutsaert, 1982) is often considered in drought monitoring and assessment. When

studying future climate, it is recommended to also contemplate temperature-related variables so that global warming can be properly taken into account (Tramblay et al., 2020; Vicente-Serrano et al., 2010). Hence, many indices have been developed to estimate drought considering AED. The most common ones are the Palmer Drought Severity Index (PDSI, Alley, 1984), that estimates soil moisture anomalies using a simplified water-balance model accounting for AED, and the Standardized Precipitation Evapotranspiration Index (SPEI, Vicente-Serrano et al., 2010), that quantifies drought by combining precipitation and AED. The choice of the index is an important source of uncertainty, as the outcomes of drought analyses often drastically differ when using alternative indices (e.g. Laimighofer and Laaha, 2022; Spinoni et al., 2021; Stagge et al., 2017; Vicente-Serrano et al., 2015).

The most common evapotranspiration-based drought indices such as SPEI and PDSI quantify drought using a simplified climatic water balance between precipitation (water supply) and atmospheric water demand (Vicente-Serrano et al., 2010). However, a variety of empirical and physically based approaches exist to calculate AED based on different sets of climatic input variables (Allen et al., 1998; Beguería et al., 2014; Vicente-Serrano et al., 2015; 2020b). It has been shown that computing future AED with methods such as Hargreaves, Thornthwaite and Penman-Monteith yields highly different results (Dewes et al., 2017; Lemaitre-Basset et al., 2022a; Milly and Dunne, 2017). In particular, empirical approaches that rely on air temperature as a surrogate for surface radiation (e.g., the Hargreaves and Thornthwaite methods) may lose validity under CO₂ concentration changes (Milly and Dunne, 2017). Furthermore, AED is commonly estimated with methods based on fixed atmospheric CO₂ levels. However, rising CO₂ concentrations influence plant behaviour in complex ways, which are not yet fully understood (Ainsworth and Long, 2005; Fatichi et al., 2016; Long et al., 2004). Hence, even more advanced methods for estimating AED, such as Penman-Monteith, can yield inaccurate values if increases in stomatal resistance are not accounted for (Milly and Dunne, 2017). Qiu et al. (2025) comprehensively summarized the effects of elevated CO₂ on plant's evapotranspiration as: (a) reduction of stomatal conductance and therefore transpiration; (b) promotion of growth and leaf area and hence increase transpiration; (c) reduction of incident radiation and, consequently, evaporation at the soil surface; (d) promotion of root growth and, therefore, increased water uptake; (e) reduction of evaporative cooling and hence warmer canopy temperature and higher vapor pressure deficit. Despite being mostly ignored in AED calculations, several approaches exist to consider vegetation response to increased CO₂ concentrations (Chitsaz et al., 2023; Sabot et al., 2022). Nevertheless, reflecting the complexity of the vegetation response to CO₂, the results largely diverge (Lemaitre-Basset et al., 2022b). As an additional layer of uncertainty, existing adjustments for CO₂-vegetation response focus mainly on reductions in stomatal conductance, while other important consequences – such as increases in leaf area – are often neglected (Liu et al., 2023; Shen et al., 2024).

When analyzing future drought with simple climate-based metrics, like SPEI and PDSI, Earth System Models (ESM) outputs such as temperature, relative humidity, wind speed and solar radiation are often used to compute AED², since ESM do not provide AED variables. However, offline drought assessment may neglect vegetation response to CO₂ while current ESM account for this effect. Past research shows that the outcomes of offline drought analyses performed with evapotranspiration-based indices often depict a much drier future in comparison to ESM outputs (Berg et al., 2017; Berg, 2022; Roderick et al., 2015; Swann et al., 2016). Acknowledging that ESM simulation of vegetation response to CO₂ remains prone to uncertainties and improvements (Green et al., 2024; Rogers et al., 2017; Vicente Serrano et al., 2020b), there is consensus that the neglect leads to altered simulations of hydrological and climatic variables, such as runoff (Lemaitre-Basset et al., 2022b; Lemordant et al., 2018) and evapotranspiration

² The term “potential evapotranspiration” is widely used in drought projections, but it is confusing and its use is not recommended (DeJonge et al., 2025). In this study, we use the term AED as done by Vicente-Serrano et al. (2020b).

² These studies are generally referred to as offline drought analysis.

(Greve et al. 2019; Scheff, 2019; Yang et al., 2019; 2023) and, as a direct consequence, drought (Tramblay et al., 2020). Nevertheless, some studies demonstrated that this effect might not be the dominant one (Scheff et al., 2021), suggesting additional causes of overestimation and increasing the uncertainty (Vicente-Serrano et al., 2022a).

While the influence of vegetation response to CO₂ in mitigating drought projections is acknowledged, the quantification of such underestimation is surprisingly missing. Neglecting vegetation response to CO₂ is a methodological gap that poses a risk to the credibility of climate change projections – whose adverse consequences are well recognized and do not require exaggeration. By systematically reviewing existing drought projection studies, this research aims to reveal the extent to which the drought literature overlooks the vegetation response to CO₂ and to quantify the resulting overestimation of drought projections. More specifically, we delve into the drought literature to verify four hypotheses: (1) vegetation response to CO₂ is not explicitly included in most drought projections; (2) vegetation response to CO₂ is generally not mentioned as a limitation or uncertainty; (3) few of the many available approaches are used to account for vegetation response to CO₂; (4) neglecting vegetation response to CO₂ causes a significant, non-negligible drought overestimation. We do this by first systematically reviewing 174 studies that assess future drought with evapotranspiration-based indices to verify if vegetation response to CO₂ is considered. After that, we quantify the overestimation extent through a meta-analysis based on a subset of papers that quantify changes in drought projections considering vegetation response to CO₂. Then, we discuss limitations and additional research gaps not addressed in this study. Finally, we conclude by providing recommendations to improve our understanding of vegetation response to CO₂ and their implications for the validity of future drought assessments.

2. Methods

The process to verify the four hypotheses is illustrated in Figure 1. With the first literature review – referred to also as the systematic literature review – hypotheses 1, 2 and partially 3 were verified. Then, with the second literature review – referred to as the meta-analysis – additional studies were identified. These studies were used to evaluate the remaining hypotheses. The PRISMA methodology for systematic reviews (Page et al., 2021) was followed by considering four phases for each literature review: (1) identification, (2) screening, (3) analysis and (4) discussion.

2.1 Identification

For the systematic review, the query was performed by combining synonyms of “drought”, “evapotranspiration” and “climate change” in the SCOPUS database up to March 2024 using the following string:

SCOPUS string query: (TITLE ("climate change") OR TITLE (warming) OR KEY ("climate change") OR KEY (warming)) AND (TITLE (evapotranspiration) OR TITLE (evaporation) OR KEY (evapotranspiration) OR KEY (evaporation)) AND (TITLE (drought) OR KEY (drought))

Given that the main objective of the second literature study was to analyze the manuscripts that discuss the inclusion of vegetation response to CO₂, additional relevant publications were searched through a snowball approach. A set of key references that introduced approaches to include vegetation response to CO₂ in the calculation of AED (Table S1) was then identified. Finally a search of the words “drought”, “climate change” and “future” within the papers that cite (a subset of) the key references was performed in Google Scholar. This second search was performed considering manuscripts available on the web search engine up to December 2024.

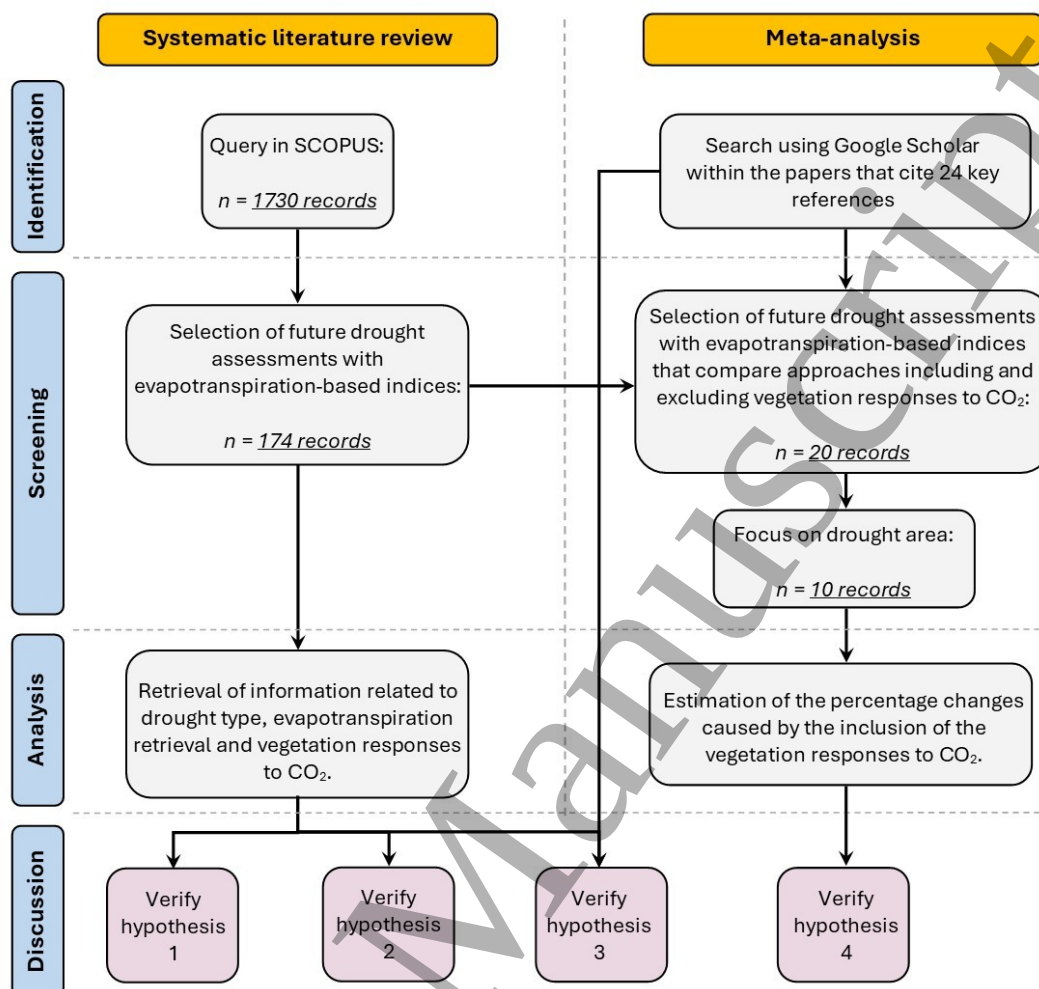


Figure 1. The complete methodology used in the systematic literature review and meta-analysis parts of the research with the four phases of the PRISMA methodology.

2.2 Screening

In the systematic review, the identified records were screened and evaluated according to the following exclusion criteria, by focusing mainly on the title and abstract of the publications and, if necessary, by a quick screening of their full text. Publications were excluded if:

- They are not written in English.
- They are not the correct type of paper (notes, letters, errata and short surveys). Hence, conference papers and articles are mainly considered. Reviews are not automatically excluded but are evaluated for the discussion, if relevant to the topic.
- They are not considering the future in the analysis.
- They are not explicitly assessing future drought periods, but for instance, focus only on water balance components, evapotranspiration and aridity trends.
- Future drought is not assessed with an evapotranspiration-based index. Hence, for example, drought projections based solely on SPI are excluded.

The same exclusion criteria applied for the records of the meta-analysis. Finally, only those papers that estimate future drought by comparing approaches both with and without considering the vegetation response to CO_2 were selected for the analysis.

2.3 Analysis

In the systematic review, information from every selected publication was extracted to

verify the first, second and partially the third hypotheses. The information retrieved, aggregated and then synthesized from each record included the year of publication, the type of drought considered, the evapotranspiration method used and whether or not vegetation response to CO₂ is included in the analysis and mentioned in the text. The full list of data collected with a detailed explanation is reported in Table S2.

The second phase consisted in an in-depth analysis of the manuscripts that include the vegetation response to CO₂ and those additionally identified through the search in Google Scholar. The additional records served also to complete verifying hypothesis 3. To verify hypothesis 4, all those manuscripts that compare future droughts estimated with and without the consideration of the vegetation response to CO₂ were carefully assessed. A key characteristic of the papers to be included in the meta-analysis was that they explicitly study the issue and discuss related results, either quantitatively or qualitatively. Hence, publications that directly compare different AED estimation methods or use the same approach but with constant or increased CO₂ concentration were mainly considered. For example, studies that compared drought evapotranspiration-based indices with soil moisture-based ones derived from ESM – that often consider the vegetation response – were excluded. Such relevant papers are mentioned when discussing the results. Given the importance of the study, in the meta-analysis, the paper of Swann et al. (2016) that quantifies the changes caused by the inclusion of vegetation response to CO₂ by comparing PDSI and precipitation minus evapotranspiration was also included. Finally, manuscripts that discuss the effect of vegetation response to CO₂ by using the outputs of global hydrological models from ISIMIP that, for some setups, contemplate these effects, were also considered.

Unfortunately, it was not possible to collect quantitative data from all the selected papers to quantify the bias related to the vegetation response to CO₂; some of the studies did not provide explicit drought estimates but only drought indices and related trends. Furthermore, the papers evaluated different drought characteristics, such as drought area, frequency, severity, intensity and so on. Only a few papers explicitly calculated the percentage changes, while others just reported general considerations. In the latter case, if possible, the absolute or percentage changes were extracted from the figures by using plotdigitizer.com/app. While some papers directly reported the CO₂ concentration values, most of them relied on Representative Concentration Pathways (RCPs; CMIP5) and Shared Socioeconomic Pathways (SSP; CMIP6). When CO₂ concentration was not explicitly reported, the corresponding CO₂ concentration value in the years of analysis as reported in Meinshausen et al. (2011, 2020) for CMIP5 and CMIP6 respectively were used. Since the search yielded a very reduced number of studies, all the available studies were considered without introducing any further selection criteria.

To verify hypothesis 4, the overestimation extent was calculated for three ranges of CO₂ concentrations: low emissions (CO₂ < 400 ppm), intermediate emissions (500 ppm < CO₂ < 600 ppm) and high emissions (CO₂ > 900 ppm). We averaged all the data points for each paper per scenario, before retrieving the final value. To verify the robustness of this estimation, the values were retrieved also considering only the global and regional studies. Furthermore, the values without averaging all the data points for each paper were calculated and reported in the supplementary materials.

3. Results

3.1 Vegetation response to CO₂ in drought projections – insights from the systematic review

After a first screening of 1730 papers using the search described in the methods section, 174 of them were analyzed. The number of drought projections with evapotranspiration-based (Fig. 2b) indices rapidly surged some years after the introduction of the SPEI in 2010 (Vicente-Serrano et al., 2010), while only one publication was found for the period before 2004 (Rind et al., 1990).

The systematic review indicates a predominance of high-emission scenarios, followed by

intermediate and low-emission pathways (Table S3), with most studies including as study period the end of the century (Table S4). Analyses are conducted primarily at national and subnational scales, whereas global assessments remain comparatively rare (Table S5). Overall, 28 countries across four continents are represented, with China and Asia emerging as the most frequently studied country and continent, respectively (Fig. 2a; Table S6). Meteorological drought is the most commonly assessed type, followed by hydrological and agricultural droughts, while a substantial fraction of studies does not explicitly specify the drought category (Table S7). In most cases, evapotranspiration is computed directly within the study, and vegetation response to CO_2 is generally not incorporated (Table S8). Among evapotranspiration-based indices, SPEI clearly dominates, followed by PDSI (Fig. S2), and precipitation is by far the most frequently hydrological variable combined with AED (Fig. S3). Penman–Monteith is the most widely used method to estimate AED, followed by Thornthwaite and Hargreaves (Fig. S4).

Out of 174 studies, only 14 (8%) include vegetation response to CO_2 in the assessment of future drought (Fig. 2b, Table S8). Seven additional papers may have considered them since they cited key literature but do not explicitly mention vegetation response to CO_2 (Fig. 2b, Table S8). Therefore, the percentage of papers that explicitly consider the vegetation response to CO_2 ranges from 8–12% of the total. Even after key publications such as Roderick et al. (2015), Milly and Dunne (2016), Swann et al. (2016) and Yang et al. (2019), the consideration of the topic is still relatively low. In the period 2020–2024, only 16 out of 110 drought assessments (15%) include vegetation response to CO_2 (Fig. 2b).

Not only the direct inclusion of the vegetation response to CO_2 is low, but only a small share of publications mention them as a limitation or a source of uncertainty. Only 18 studies (12%) – among those that did not directly and clearly include vegetation response to CO_2 – somehow mentioned the limitation or uncertainty or cited related key literature (Fig. 2b, Table S8). It is important to underline that, in the systematic review, 91 out of 156 papers (57.5%) that did not include vegetation response to CO_2 considered high emission scenarios by the end of the century with $\text{CO}_2 > 900$ ppm (Fig. 2c). Among them, 28 apply the Thornthwaite method to estimate future AED that, being highly sensitive to increased temperatures, drastically overestimates future AED and hence drought (Aadhar and Mishra, 2020; 2022; Milly and Dunne, 2017). Even if the mechanisms and processes behind the vegetation response to CO_2 are still debated (e.g. Vicente-Serrano et al., 2022a), the literature suggests that avoiding their inclusion leads to an overestimation of AED and drought (Berg et al., 2017; Berg, 2022; Roderick et al., 2015; Swann et al., 2016). Therefore, the vast majority of the drought assessments that considered evapotranspiration-based drought indices overestimated future drought.

Another key insight is that most studies considering vegetation response to CO_2 use the simple linear modification of the Penman–Monteith equation as proposed by Yang et al. (2019) (Fig. 2c). The second most adopted approach is the energy-based one proposed by Milly and Dunne (2016). An et al. (2024) applied the procedure suggested by Y. Kim et al. (2021; 2023) which is improved compared to Yang et al. (2019) as it takes into account the land–atmosphere feedback. Similarly, Shen et al. (2024) considered the approach proposed by Liu et al. (2023), which represents an advancement since it considers vegetation changes by incorporating the Leaf Area Index. S. Li et al. (2023) expressed the concern that the linear equation of Yang et al. (2019) considers only the reduction in stomatal conductance caused by increased CO_2 but disregards vegetation dynamics. To verify the extent of the uncertainty related to this simplification, they compared the canopy conductance estimated with the empirical statistical model of Yang et al. (2019) with an optimal model and found positive correlations, especially in the middle-high emissions scenarios over most global land. Another way to include vegetation response to CO_2 in drought projections is by avoiding directly calculating AED but instead relying on external data or software. In this way, some studies indirectly consider vegetation response to CO_2 response by using outputs from ESM (e.g. Burke and Brown, 2008; Burke, 2011; Cook et al., 2015; Swann et al., 2016; Vicente-Serrano et al., 2022b; Zhao and Dai, 2015;

2022) or global hydrological models from ISIMIP (e.g. Satoh et al., 2022; Wang et al., 2022a) or other crop or hydrological models such as the Soil and Water Assessment Tool (e.g. B. Li et al., 2023; Villani et al., 2024) and SIMETAW (Mancosu et al., 2016; Masia et al., 2021).

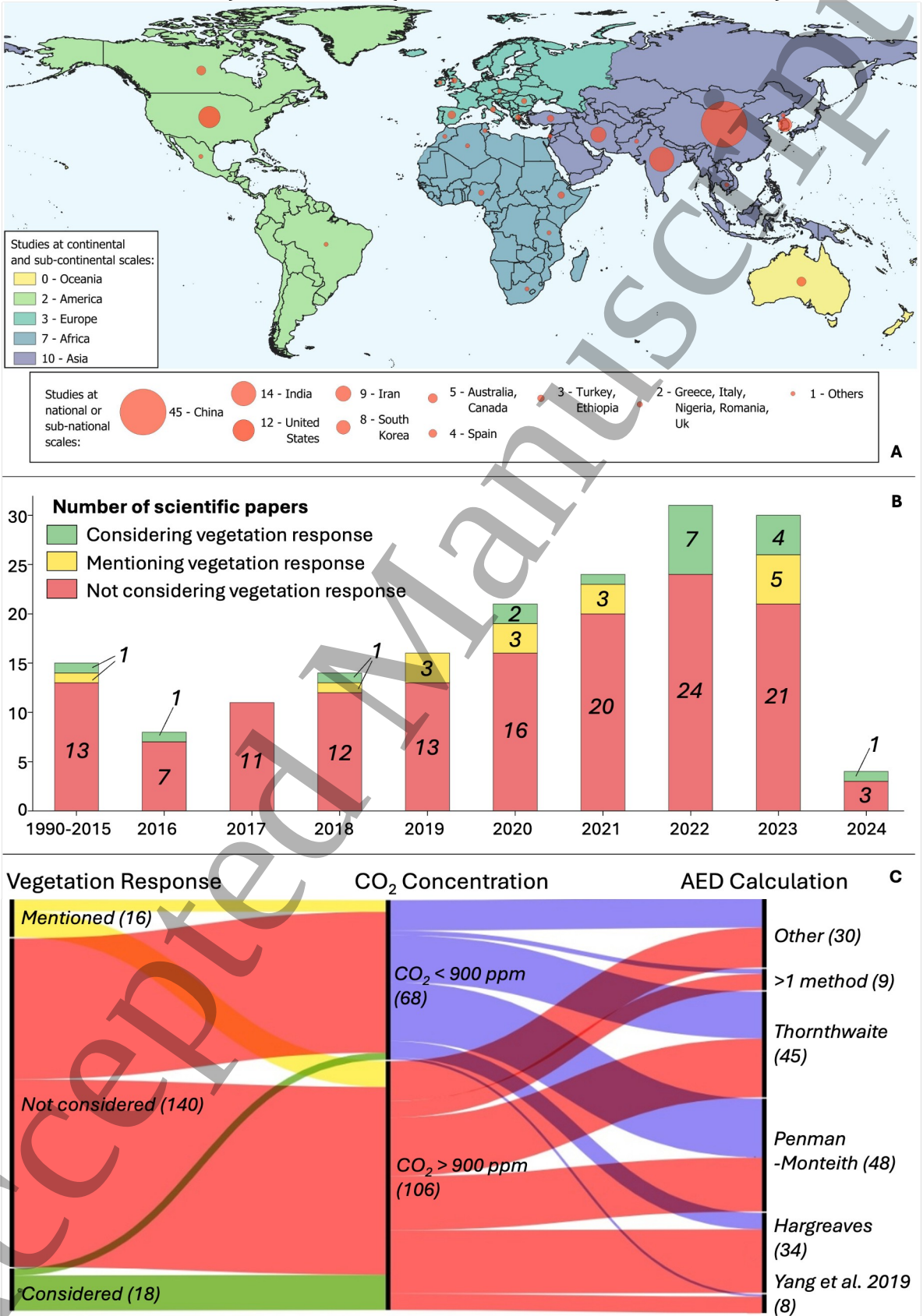


Figure 2. Outcomes of the systematic literature review. A) The distribution of the studies included in the systematic review at (sub)continental scale – represented with categorized colors – and (sub)national scale – represented with dimensions of the red dot. B) Year of publication of the papers considered in the systematic review phase (the search was performed in March 2024) with the number of papers that either include – meaning that they used a modified AED retrieval method – or mention – i.e. they discuss the limitations or they refer to key references – vegetation response to CO₂. C) Alluvial plot³ to show the number of papers that consider and mention vegetation response to CO₂, whether they consider elevated CO₂ concentration scenarios and the method to retrieve AED. Notice that numbers are slightly different from the text as in the figure the unclear studies were assigned to the most likely category (“considered”, “mentioned”).

3.2 The effect of vegetation response to CO₂ on drought projections – insights from the meta-analysis

Building on the first part of the analysis, which evaluated the share of drought projections neglecting vegetation response to CO₂, the second part considers a subset of records to quantify the resulting bias. After having completed the second search, only the 20 publications that directly compare drought projections considering both cases of including/excluding the vegetation response to CO₂ were selected. However, many studies investigate different drought attributes and are therefore difficult to compare. Finally, the quantification was based on the changes in projected drought area due to the inclusion of vegetation response to CO₂ considering 10 publications (Table S9, Fig. 3a, c). The literature analyzed agrees that disregarding the vegetation response to CO₂ leads to an overestimation of future drought area (Fig. 3d, S5). Most of the changes (86%) are above -20% and feature a fairly extensive range with a minimum of -42.6% (Fig. 3d). Most of the outliers are the data points extracted from study 2 – S. Jiang et al. (2022) that also for the historical period found unusual reductions below -30% caused by the inclusion of the vegetation response to CO₂. A possible explanation for this could be that their study area (i.e. the Chinese drylands) is more sensitive to AED changes (as in study 1 – Aadhar & Mishra, 2020). The data point collected from study 6 – Swann et al. (2016) is another outlier, with an estimated change of -33% at elevated CO₂ concentration. Notably, this study differs from the others by estimating drought area using PDSI without vegetation response to CO₂ and precipitation minus evaporation when accounting for it. Study 1 – Aadhar & Mishra (2020) also found a substantial change for hyper-arid South Asia for which the change reaches -34%, in line with the values of study 2 – S. Jiang et al. (2022). Analyzing in detail the outputs of study 1 – Aadhar & Mishra (2020), it is evident how climate type strongly influences the effect of the vegetation response to CO₂; while large sensitivities are found in hyper-arid and arid climate zones, the changes are limited to approximately 3% for the humid climate. In addition to study 2 – S. Jiang et al. (2022), study 10 – Wang et al. (2022a) reported high historical changes of 5.8–9.4%, depending on the drought severity threshold. Specifically, study 10 – Wang et al. (2022a) used the outputs of ISIMIP global hydrological models and compared them with the standard PDSI index, suggesting that the vegetation response to CO₂ is not the only difference in the models. Except for these studies, in the group with historical CO₂ concentrations, the differences are below 2.4% for study 7 – Yang et al. (2020), study 4 – D. Kim et al. (2021) and study 3 – H. Jiang et al. (2022), while they are negligible considering all the outputs from study 1 – Aadhar & Mishra (2020) and study 5 – D. Kim et al. (2023). As expected, they increase in the future as CO₂ concentration rises.

As reported in Table S14, the effect of neglecting vegetation response to CO₂ in the estimation of future drought area is quantified in $6.0 \pm 11.3\%$, $8.7 \pm 11.0\%$ and $17.4 \pm 10.6\%$ for the historical (CO₂ < 400 ppm), intermediate (500 ppm < CO₂ < 600 ppm) and high emission scenarios (CO₂ > 900 ppm) respectively (Fig. 3d). The other options that were considered to estimate the bias yield similar results (Tables S11–16). More specifically, comparing global (studies 6–10) and regional (studies 1–5) papers results in differences in changes below 2%, though a higher standard deviation is observed for the regional studies (Tables S13, S16).

³ The plot was created in rawgraphs.io

Considering the average of the papers instead of all the data points of Table S9 results in higher biases for the low and high emission scenarios (Tables S11, S14). This is mostly caused by the higher importance assigned to the data point from study 2 – S. Jiang et al. (2022) and to study 6 – Swann et al. (2016) for the low and high emission scenarios, respectively. On the other hand, the overestimation for the intermediate scenario is slightly reduced.

Analyzing additional papers (Table S10), different outcomes emerge, confirming the uncertainty around this topic and the range of changes reported in Figure 3d. For example, some of them found negligible changes caused by vegetation response to CO₂ (Cook et al., 2015; Zeng et al., 2023). However, most of the studies confirmed the overestimation of drought as a result of neglecting the vegetation response to CO₂, with consistent – yet less pronounced – changes (e.g. Ficklin et al., 2022; Lehner et al., 2017; S. Li et al., 2023; Su et al., 2024; Xu et al., 2024). Finally, a subset of studies reported not only an overestimation of drying trends after the inclusion of the vegetation response to CO₂ but also an opposite sign of change, with wetter future conditions in some parts of the study areas. For example, Sun et al. (2024) found similar trend patterns with both cases, except in northeastern China, where including vegetation response to CO₂ reversed the signal from drying to wetting. Similarly, Shen et al. (2024) found significant changes in southwestern China when considering vegetation response to CO₂, shifting from a drying trend with the standard Penman-Monteith equation towards negligible or wetting trends considering vegetation response to CO₂ with SPEI or PDSI, respectively. An et al. (2024) analyzed global drought patterns and trends by applying the methods of Yang et al. (2019) and Y. Kim et al. (2021; 2023) and, at the global scale, found the strongest drying trends when using the standard Penman-Monteith approach, followed by the method of Yang et al. (2019). Interestingly, when considering the equations of Y. Kim et al. (2021; 2023) to incorporate the vegetation response to CO₂, they found a slight wetting global trend. Focusing on smaller scales, in the same publication (An et al., 2024), the Penman-Monteith approach proposed by Yang et al. (2019) resulted in the opposite sign of change for 14.7% of the land, while this percentage increased to 22.6% when considering Y. Kim et al. (2021; 2023). While much more research is certainly needed, it is revealing that the two studies (An et al., 2024; Shen et al., 2024) that used state-of-the-art approaches in land-atmosphere feedback (Y. Kim et al., 2021; 2023) or incorporate Leaf Area Index (Liu et al., 2023) showed the strongest differences compared to standard Penman-Monteith – higher frequency of sign reversals compared to Yang et al. (2019).

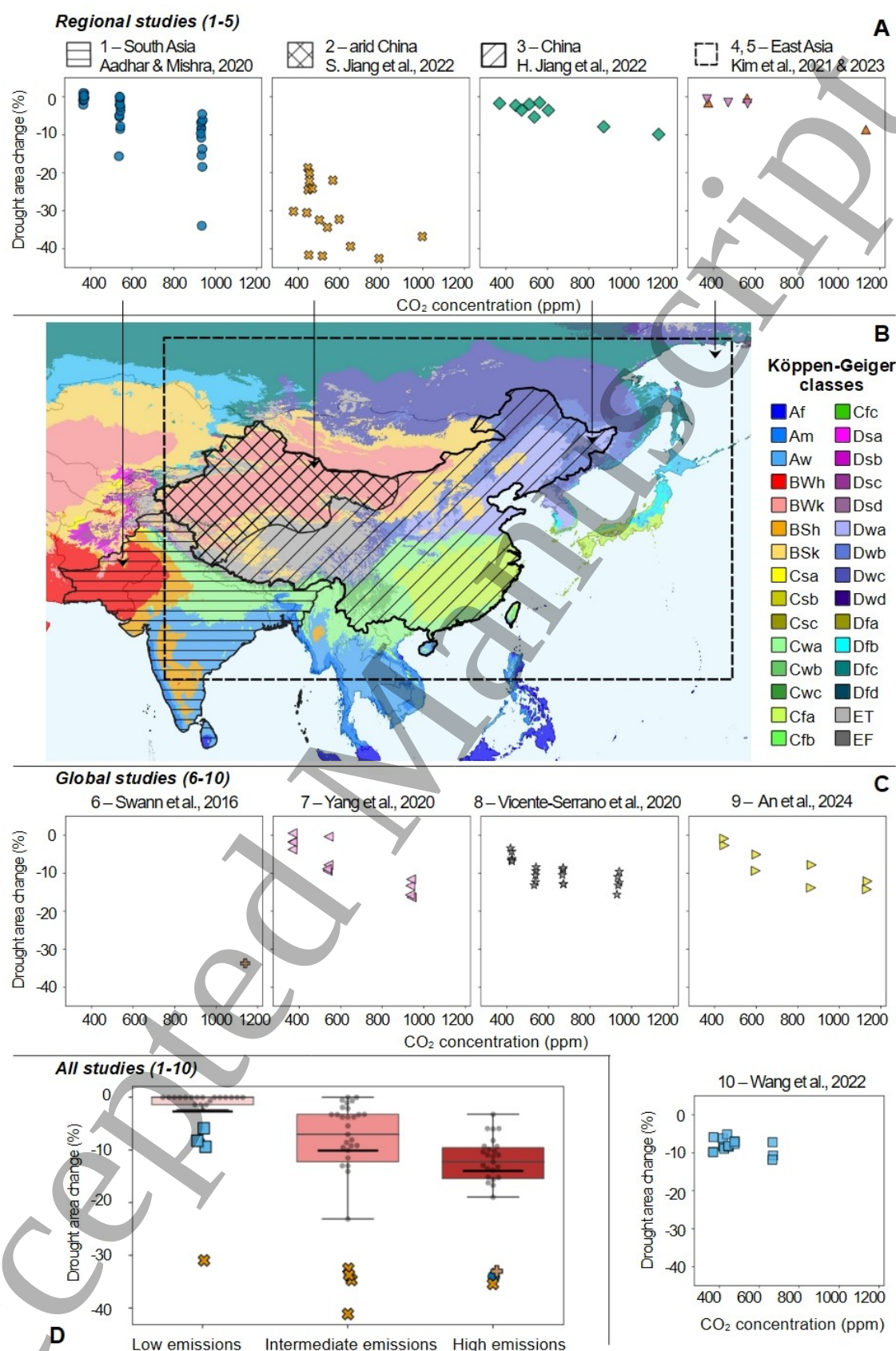


Figure 3. Outcomes of the meta-analysis. B) The map of South and East Asia represents the study area of the five regional publications (Table S9) used in the meta-analysis, with the Köppen-Geiger climate classification from Beck et al. (2018) as background. A) The first row of scatterplots refer to the five regional studies; C) under the map are reported the scatterplots of the five global studies and D) a box plot summarising the results of all the studies. Each scatterplot represents the estimated percentage

changes in drought area against CO₂ concentration (ppm) caused by the inclusion of the vegetation response to CO₂. Data entries from different sources are coloured and marked differently. For each paper, the data is extracted from text and figures. Note that data entries vary among the 10 publications, ranging from 1 to 36 values, as reported in Table S9. The complete scatterplot is reported in the supplementary materials (Fig. S5). The box plot considers the same data but grouped to consider the historical (CO₂ < 400 ppm), intermediate (500 ppm < CO₂ < 600 ppm) and high-emission (CO₂ > 900 ppm) CO₂ concentration levels. Grey dots represent the data while the horizontal black bar the average values. The outliers from study, 1, 2, 6 and 10 have the same formatting as in the scatterplots.

4. Discussion

4.1 Vegetation response to CO₂ omission as a critical methodological gap in drought projections

The neglect of vegetation response to CO₂ in evapotranspiration-based drought projections is surprising since the plant physiological effect of rising CO₂ have been extensively debated for decades in plant- and water-related disciplines (Field et al., 1995; Jarvis, 1976; Rind et al., 1990). For example, this type of research is fully considered in the latest Assessment Report of the Intergovernmental Panel on Climate Change and in the same ESM whose outputs are used in offline drought projections (Rogers et al., 2017). Furthermore, only a small fraction of the approaches proposed in the literature are used to simulate vegetation response to CO₂ when deriving AED (Table S1, Chitsaz et al., 2023; Sabot et al., 2022). As new methods become available and more studies test, apply and compare them, researchers and practitioners will have access to improved and alternative methods. Incorporating vegetation response to CO₂ into AED estimates may also become increasingly straightforward, either through direct computation using tools such as PyET (Vremec et al., 2024) or via global model outputs and datasets (e.g. Peiris and Döll, 2023). Recent developments suggest that ongoing research is already exploring alternatives to the approach of Yang et al. (2019). A major step forward would be the inclusion of AED (evspsblpot) as a standard ESM output by the modelling community (CMIP). Our systematic review clearly shows that current drought research largely neglects vegetation response to CO₂, even when using evapotranspiration-based indices that should explicitly account for them. The implications of this omission are not limited to hazard assessments: Wang and Sun (2023) showed that excluding vegetation response to CO₂ can lead to an overestimation of drought-exposed population and GDP by up to 8.5% and 6.7% by 2050, respectively.

4.2 Limitations and sources of uncertainty

Although the analysis was conducted within a transparent and reproducible methodological framework, some limitations should be acknowledged. First, we recognize that some papers that use evapotranspiration-based indices to assess future drought are not found through the proposed query (e.g. H. Li et al., 2021; Spinoni et al., 2021). Nevertheless, we assume that the identified records are representative and unbiased to answer our research questions. Second, our study focused exclusively on drought projections based on evapotranspiration-based indices, while a comprehensive evaluation of future drought should extend to the full spectrum of drought indices. For instance, drought projections that apply soil moisture indices generally incorporate vegetation response to CO₂ as they typically use direct ESM outputs (e.g. Aadhar and Mishra, 2020). On the other hand, drought projections relying solely on precipitation-based indices do not explicitly account for either rising temperatures or vegetation response to CO₂. Third, the quantification of the bias associated with neglecting vegetation response to CO₂ is currently constrained by the limited number of studies adopting alternative approaches. As more research applies and compares these methods, it will become possible to evaluate more robust changes across climates, regions, indices, and drought characteristics such as frequency and severity. Despite these limitations, this assessment represents a necessary step toward fostering a more comprehensive and critical discussion of vegetation–CO₂ interactions in future drought projections.

Beyond our analysis, substantial uncertainties remain regarding the understanding and

simulation of vegetation response to rising CO₂. These include feedback and synergies of elevated CO₂ with concurrent changes in future climate (i.e. temperature and drought, Kirschbaum and McMillan, 2018; Swann, 2018; Wang et al., 2022b; Vicente-Serrano et al., 2020b), as well as processes at multiple scales such as cell, leaf, canopy and above (Fatichi et al., 2016; Matthews and Lawson, 2018; Miralles et al. 2025). Vegetation types and species respond differently to elevated CO₂ and this is rarely represented in current drought projections (Swann, 2018). Many approaches exist to simulate stomatal conductance considering the vegetation functional type (De Kauwe et al., 2015; Manzoni et al., 2011; Zhou et al., 2019) which might improve the reliability of drought projections. Rising CO₂ is mainly expected to influence vegetation water-use efficiency both through the CO₂ stomatal conductance suppression and the CO₂ fertilization effect on photosynthesis, which are spatially distinct (Zhang et al., 2022). While the stomatal conductance suppression is explicitly simulated in the modifications of the Penman-Monteith approach⁴, other responses such as increasing Leaf Area Index are generally omitted in drought projections, with few exceptions (e.g. Liu et al., 2023). Finally, the effects of rising CO₂ on crop yields remain uncertain, not only in terms of total production (McGrath and Lobell, 2013) but also regarding physiological processes that influence crop nutritional quality (Toresi et al., 2020). Overall, the uncertainties discussed above – ranging from methodological choices in AED estimation to vegetation-type variability and structural model assumptions – highlight both the complexity of representing vegetation–CO₂ interactions and the need for further research.

5. Conclusions

Despite clear evidence from ecophysiological studies, our meta-analysis reveals that the vegetation response to CO₂ remains largely absent from most drought projections. Neglecting plant physiology leads to a systematic overestimation of future drought extent by 17.4% under high-emissions scenarios. The overestimation is more compelling in dryland regions where policy decisions on water allocation and agricultural planning are highly sensitive to such projections. As climate adaptation and risk planning increasingly rely on drought projections, our findings highlight a critical gap in current modelling practices. In particular, the widespread reliance on offline estimations of AED — without accounting for CO₂-induced stomatal regulation — may misguide both research and policy on future water planning and management. More importantly, this methodological gap could cast doubt on climate change implications—including drought increases in many regions of the world. Regarding existing drought projections, we recommend caution in their use if they neglect vegetation response to CO₂ especially in dry climates, while we call for using at least the approaches proposed by Milly and Dunne (2016) and Yang et al. (2019) as baseline to develop such studies in the future. Directly exporting AED values from ESM should be considered in CMIP7 since it would be a great step towards enhanced consistency between these model outputs and offline drought projections. More broadly, we endorse further interdisciplinary collaboration between plant ecophysiologicalists and ecohydrologists to better understand and represent CO₂-vegetation feedback (Wilkening et al., 2024). By avoiding the neglect of vegetation response to CO₂, the scientific community will be able to provide actionable, accurate information needed for climate-resilient water and land management in a warming world.

Conflict of interest

The authors declare that there is no conflicts of interest.

Credit

Conceptualization: LV

Methodology: LV, LP, GC, DP, FJ, BVS, NG, EL, EAY

⁴Which are the most common methods to simulate vegetation response (e.g. Yang et al., 2019).

Investigation: LV, LP, EAY, BVS, NG, IB, EL, AB, MFA, MB

Validation: LV, NG

Data curation: LV

Writing original draft: LV with significant contribution of LP, GC, DP, BVS, AB, MD

Writing – Review and editing: all the authors

Visualization: LV, LP, EL

Supervision: EB, AVG, DP

References

- [1] Aadhar, S., & Mishra, V. (2020). Increased drought risk in South Asia under warming climate: Implications of uncertainty in potential evapotranspiration estimates. *Journal of Hydrometeorology*, 21(12), 2979-2996.
- [2] Aadhar, S., & Mishra, V. (2022). Challenges in drought monitoring and assessment in India. *Water Security*, 16, 100120.
- [3] Ainsworth, E. A., & Long, S. P. (2005). What have we learned from 15 years of free-air CO₂ enrichment (FACE)? A meta-analytic review of the responses of photosynthesis, canopy properties and plant production to rising CO₂. *New phytologist*, 165(2), 351-372.
- [4] Allen, R.G., Pereira, L., Raes, D., & Smith, M. (1998). Crop evapotranspiration: guidelines for computing crop water requirements. FAO Drainage and Irrigation Paper 56. Food and Agriculture Organization, Rome
- [5] Alley, W. M. (1984). The Palmer drought severity index: limitations and assumptions. *Journal of Applied Meteorology and Climatology*, 23(7), 1100-1109.
- [6] An, X., Zhang, Y., Sun, S., Chai, R., Bi, Z., Li, J., ... & Chen, H. (2024). Future drought overestimations due to no constraints of CO₂ physiological effect and land-atmosphere coupling on potential evapotranspiration. *Environmental Research Letters*, 19(12), 124031.
- [7] Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., & Wood, E. F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific data*, 5(1), 1-12.
- [8] Begueria, S., Vicente-Serrano, S. M., Reig, F., & Latorre, B. (2014). Standardized precipitation evapotranspiration index (SPEI) revisited: Parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International Journal of Climatology*, 34(10), 3001–3023. <https://doi.org/10.1002/joc.3887>
- [9] Berg, A., Sheffield, J., & Milly, P. C. (2017). Divergent surface and total soil moisture projections under global warming. *Geophysical Research Letters*, 44(1), 236-244.
- [10] Berg, A. (2022). Bridging the gap between simple metrics and model simulations of climate change impacts on land hydrology. *Earth's Future*, 10(12), e2022EF003259.
- [11] Brutsaert, W. (1982). *Evaporation into the Atmosphere: Theory, History and Applications*. Dordrecht: D. Reidel
- [12] Burke, E. J. (2011). Understanding the sensitivity of different drought metrics to the drivers of drought under increased atmospheric CO₂. *Journal of Hydrometeorology*, 12(6), 1378-1394.
- [13] Burke, E. J., & Brown, S. J. (2008). Evaluating uncertainties in the projection of future drought. *Journal of Hydrometeorology*, 9(2), 292-299.
- [14] Chitsaz, N., Guan, H., Shanafield, M., & Batelaan, O. (2023). Evaluating CO₂ effects on semi-empirical and empirical stomatal conductance simulation in land surface models. *Journal of Hydrology*, 620, 129385.
- [15] Cook, B. I., Ault, T. R., & Smerdon, J. E. (2015). Unprecedented 21st century drought risk in the American Southwest and Central Plains. *Science advances*, 1(1), e1400082.
- [16] Damkjaer, S., & Taylor, R. (2017). The measurement of water scarcity: Defining a meaningful indicator. *Ambio*, 46(5), 513-531.
- [17] De Kauwe, M. G., Zhou, S. X., Medlyn, B. E., Pitman, A. J., Wang, Y. P., Duursma, R. A., & Prentice, I. C. (2015). Do land surface models need to include differential plant species responses to drought? Examining model predictions across a mesic-xeric gradient in Europe. *Biogeosciences*, 12(24), 7503-7518.
- [18] DeJonge, K. C., Allen, R., Kilic, A., Thorp, K. R., Kukal, M., Marek, G., ... & Trout, T. (2025). Evapotranspiration terminology and definitions. *Irrigation and Drainage Engineering*, 15(5).
- [19] Dewes, C. F., Rangwala, I., Barsugli, J. J., Hobbins, M. T., & Kumar, S. (2017). Drought risk assessment under climate change is sensitive to methodological choices for the estimation of evaporative demand. *PloS one*, 12(3), e0174045.
- [20] Fatichi, S., Pappas, C., & Ivanov, V. Y. (2016). Modeling plant–water interactions: an ecohydrological overview from the cell to the global scale. *Wiley Interdisciplinary Reviews: Water*, 3(3), 327-368.
- [21] Ficklin, D. L., Null, S. E., Abatzoglou, J. T., Novick, K. A., & Myers, D. T. (2022). Hydrological intensification will increase the complexity of water resource management. *Earth's Future*, 10(3), e2021EF002487.
- [22] Field, C. B., Jackson, R. B., & Mooney, H. A. (1995). Stomatal responses to increased CO₂: implications from the plant to the global scale. *Plant, Cell & Environment*, 18(10), 1214-1225.
- [23] Green, J. K., Zhang, Y., Luo, X., & Keenan, T. F. (2024). Systematic underestimation of canopy conductance sensitivity to drought by Earth System Models. *AGU Advances*, 5(1), e2023AV001026.
- [24] Greve, P., Roderick, M. L., Ukkola, A. M., & Wada, Y. (2019). The aridity Index under global warming.

- Environmental Research Letters, 14(12), 124006. <https://doi.org/10.1088/1748-9326/ab5046>
- [25] Hagenlocher, M., Naumann, G., Meza, I., Blauhut, V., Cotti, D., Döll, P., ... & Wens, M. (2023). Tackling growing drought risks—the need for a systemic perspective. *Earth's Future*, 11(9), e2023EF003857.
- [26] Han, J., & Singh, V. P. (2023). A review of widely used drought indices and the challenges of drought assessment under climate change. *Environmental Monitoring and Assessment*, 195(12), 1438.
- [27] Jarvis, P. (1976). The interpretation of the variations in leaf water potential and stomatal conductance found in canopies in the field. *Philosophical Transactions of the Royal Society of London. B, Biological Sciences*, 273(927), 593-610.
- [28] Jiang, H., Wang, G., Li, S., Ullah, W., Amankwah, S. O. Y., & Lu, J. (2022). Effect of CO₂ concentration on drought assessment in China. *International Journal of Climatology*, 42(15), 7465-7482.
- [29] Jiang, S., Zhou, J., Wang, G., Lin, Q., Chen, Z., Wang, Y., & Su, B. (2022). Cropland Exposed to Drought Is Overestimated without Considering the CO₂ Effect in the Arid Climatic Region of China. *Land*, 11(6), 881.
- [30] Kchouk, S., Melsen, L. A., Walker, D. W., & Van Oel, P. R. (2022). A geography of drought indices: mismatch between indicators of drought and its impacts on water and food securities. *Natural Hazards and Earth System Sciences*, 22(2), 323-344.
- [31] Kim, D., Chun, J. A., Yeo, J. H., & Ha, K. J. (2023). Divergent flash drought risks indicated by evaporative stress and soil moisture projections under warming scenarios. *Environmental Research Letters*, 18(9), 094023.
- [32] Kim, D., Ha, K. J., & Yeo, J. H. (2021). New drought projections over East Asia using evapotranspiration deficits from the CMIP6 warming scenarios. *Earth's Future*, 9(6), e2020EF001697.
- [33] Kim, Y., Garcia, M. & Johnson, M. S. (2023). Land-atmosphere coupling constrains increases to potential evaporation in a warming climate: implications at local and global scales. *Earth's Future* 11 e2022EF002886
- [34] Kim, Y., Garcia, M., Morillas, L., Weber, U., Black, T. A. & Johnson, M. S. (2021). Relative humidity gradients as a key constraint on terrestrial water and energy fluxes. *Hydrol. Earth Syst. Sci.* 25 5175–91
- [35] Kirschbaum, M. U., & McMillan, A. M. (2018). Warming and elevated CO₂ have opposing influences on transpiration. Which is more important?. *Current Forestry Reports*, 4, 51-71.
- [36] Laimighofer, J., & Laaha, G. (2022). How standard are standardized drought indices? Uncertainty components for the SPI & SPEI case. *Journal of Hydrology*, 613, 128385.
- [37] Lehner, F., Coats, S., Stocker, T. F., Pendergrass, A. G., Sanderson, B. M., Raible, C. C., & Smerdon, J. E. (2017). Projected drought risk in 1.5 C and 2 C warmer climates. *Geophysical Research Letters*, 44(14), 7419-7428.
- [38] Lemaitre-Basset, T., Oudin, L., & Thirel, G. (2022b). Evapotranspiration in hydrological models under rising CO₂: a jump into the unknown. *Climatic Change*, 172(3–4), 1–19. <https://doi.org/10.1007/s10584-022-03384-1>
- [39] Lemaitre-Basset, T., Oudin, L., Thirel, G., & Collet, L. (2022a). Unraveling the contribution of potential evaporation formulation to uncertainty under climate change. *Hydrology and Earth System Sciences*, 26(8), 2147-2159.
- [40] Lemordant, L., Gentine, P., Swann, A. S., Cook, B. I., & Scheff, J. (2018). Critical impact of vegetation physiology on the continental hydrologic cycle in response to increasing CO₂. *Proceedings of the National Academy of Sciences*, 115(16), 4093-4098.
- [41] Li, B., Tan, L., Zhang, X., Qi, J., Marek, G. W., Li, Y., ... & Chen, Y. (2023). Modeling streamflow response under changing environment using a modified SWAT model with enhanced representation of CO₂ effects. *Journal of Hydrology: Regional Studies*, 50, 101547.
- [42] Li, H., Li, Z., Chen, Y., Xiang, Y., Liu, Y., Kayumba, P. M., & Li, X. (2021). Drylands face potential threat of robust drought in the CMIP6 SSPs scenarios. *Environmental Research Letters*, 16(11), 114004.
- [43] Li, S., Wang, G., Chai, Y., Miao, L., Hagan, D. F. T., Sun, S., ... & Guan, Z. (2023). Increasing vapor pressure deficit accelerates land drying. *Journal of Hydrology*, 625, 130062.
- [44] Liu, Z., Wang, T., Li, C., Yang, W., & Yang, H. (2023). A physically-based potential evapotranspiration model for global water availability projections. *Journal of Hydrology*, 622, 129767. <https://doi.org/10.1016/j.jhydrol.2023.129767>
- [45] Long, S. P., Ainsworth, E. A., Rogers, A., & Ort, D. R. (2004). Rising atmospheric carbon dioxide: plants FACE the future. *Annu. Rev. Plant Biol.*, 55(1), 591-628.
- [46] Mancosu, N., Spano, D., Orang, M., Sarreshteh, S., & Snyder, R. L. (2016). SIMETAW#-a model for agricultural water demand planning. *Water resources management*, 30, 541-557.
- [47] Manzoni, S., Vico, G., Katul, G., Fay, P. A., Polley, W., Palmroth, S., & Porporato, A. (2011). Optimizing stomatal conductance for maximum carbon gain under water stress: a meta-analysis across plant functional types and climates. *Functional Ecology*, 25(3), 456-467.
- [48] Masia, S., Trabucco, A., Spano, D., Snyder, R. L., Sušnik, J., & Marras, S. (2021). A modelling platform for climate change impact on local and regional crop water requirements. *Agricultural Water Management*, 255, 107005.
- [49] Matthews, J. S., & Lawson, T. (2018). Climate change and stomatal physiology. *Annual plant reviews online*, 713-752.
- [50] McGrath, J. M., & Lobell, D. B. (2013). Regional disparities in the CO₂ fertilization effect and implications for crop yields. *Environmental research letters*, 8(1), 014054.
- [51] McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology* (Vol. 17, No. 22, pp. 179-183).
- [52] Meinshausen, M., Nicholls, Z. R., Lewis, J., Gidden, M. J., Vogel, E., Freund, M., ... & Wang, R. H. (2020). The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500. *Geoscientific Model*

- Development, 13(8), 3571-3605.
- [53] Meinshausen, M., Smith, S. J., Calvin, K., Daniel, J. S., Kainuma, M. L., Lamarque, J. F., ... & van Vuuren, D. P. (2011). The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic change*, 109, 213-241.
- [54] Milly, P. C. D. & Dunne, K. A. (2017). A hydrologic drying bias in water-resource impact analyses of anthropogenic climate change. *JAWRA Journal of the American Water Resources Association*, 53(4), 822-838.
- [55] Milly, P. C. D. & Dunne, K. A. (2016). Potential evapotranspiration and continental drying. *Nature Clim Change* 6, 946-949.
- [56] Miralles, D. G., Vilà-Guerau de Arellano, J., McVicar, T. R., & Mahecha, M. D. (2025). Vegetation-climate feedbacks across scales. *Annals of the New York Academy of Sciences*.
- [57] Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of hydrology*, 391(1-2), 202-216.
- [58] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *International journal of surgery*, 88, 105906.
- [59] Peiris, T. A., & Döll, P. (2023). Improving the quantification of climate change hazards by hydrological models: a simple ensemble approach for considering the uncertain effect of vegetation response to climate change on potential evapotranspiration. *Hydrology and Earth System Sciences*, 27(20), 3663-3686.
- [60] Qiu, R., Katul, G. G., Zhang, L., Qin, S., & Jiang, X. (2025). The effects of changing environments, abiotic stresses, and management practices on cropland evapotranspiration: A review. *Reviews of Geophysics*, 63(1), e2024RG000858.
- [61] Rind, D., Goldberg, R., Hansen, J., Rosenzweig, C., & Ruedy, R. (1990). Potential evapotranspiration and the likelihood of future drought. *Journal of Geophysical Research: Atmospheres*, 95(D7), 9983-10004.
- [62] Roderick, M. L., Greve, P., & Farquhar, G. D. (2015). On the assessment of aridity with changes in atmospheric CO₂. *Water Resources Research*, 51(7), 5450-5463.
- [63] Rogers, A., Medlyn, B. E., Dukes, J. S., Bonan, G., von Caemmerer, S., Dietze, M. C., ... & Zaehle, S. (2017). A roadmap for improving the representation of photosynthesis in Earth system models. *New Phytologist*, 213(1), 22-42.
- [64] Sabot, M. E., De Kauwe, M. G., Pitman, A. J., Medlyn, B. E., Ellsworth, D. S., Martin-StPaul, N. K., ... & Serbin, S. P. (2022). One stomatal model to rule them all? Toward improved representation of carbon and water exchange in global models. *Journal of Advances in Modeling Earth Systems*, 14(4), e2021MS002761.
- [65] Satoh, Y., Yoshimura, K., Pokhrel, Y., Kim, H., Shioyama, H., Yokohata, T., ... & Oki, T. (2022). The timing of unprecedented hydrological drought under climate change. *Nature communications*, 13(1), 3287.
- [66] Scheff, J. (2019). A unified wetting and drying theory. *Nature Clim Change* 9, 9-10.
<https://doi.org/10.1038/s41558-018-0372-x>
- [67] Scheff, J., Mankin, J. S., Coats, S., & Liu, H. (2021). CO₂-plant effects do not account for the gap between dryness indices and projected dryness impacts in CMIP6 or CMIP5. *Environmental Research Letters*, 16(3), 034018.
- [68] Shen, J., Yang, H., Liu, Z., Li, C., Li, S., Cui, Y., & Yang, D. (2024). Assessment of meteorological drought in a changing environment: An example in the Upper Yangtze River. *Journal of Geophysical Research: Atmospheres*, 129(20), e2024JD041019.
- [69] Spinoni, J., Barbosa, P., Buccignani, E., Cassano, J., Cavazos, T., Cescatti, A., ... & Dosio, A. (2021). Global exposure of population and land-use to meteorological droughts under different warming levels and SSPs: A CORDEX-based study. *International Journal of Climatology*, 41(15), 6825-6853.
- [70] Stagge, J. H., Kingston, D. G., Tallaksen, L. M., & Hannah, D. M. (2017). Observed drought indices show increasing divergence across Europe. *Scientific Reports*, 7(1), 1-10.
- [71] Su, X., Huang, G., Wang, L., & Wang, T. (2024). Global drought changes and attribution under carbon neutrality scenario. *Climate Dynamics*, 62(8), 7851-7868.
- [72] Sun, S., Chai, R., Zhang, Y., Wang, J., Bi, Z., Li, J., ... & Chen, H. (2024). On the attribution of historical and future dryness/wetness changes in China incorporating surface resistance response to elevated CO₂. *Global and Planetary Change*, 234, 104380.
- [73] Swann, A. L. (2018). Plants and drought in a changing climate. *Current Climate Change Reports*, 4, 192-201.
- [74] Swann, A. L., Hoffman, F. M., Koven, C. D., & Randerson, J. T. (2016). Plant responses to increasing CO₂ reduce estimates of climate impacts on drought severity. *Proceedings of the National Academy of Sciences*, 113(36), 10019-10024.
- [75] Toreti, A., Deryng, D., Tubiello, F. N., Müller, C., Kimball, B. A., Moser, G., ... & Rosenzweig, C. (2020). Narrowing uncertainties in the effects of elevated CO₂ on crops. *Nature Food*, 1(12), 775-782.
- [76] Trambly, Y., Koutroulis, A., Samaniego, L., Vicente-Serrano, S. M., Volaire, F., Boone, A., ... & Polcher, J. (2020). Challenges for drought assessment in the Mediterranean region under future climate scenarios. *Earth-science reviews*, 210, 103348.
- [77] Van Loon, A. F., Gleeson, T., Clark, J., Van Dijk, A. I., Stahl, K., Hannaford, J., ... & Van Lanen, H. A. (2016a). Drought in the Anthropocene. *Nature Geoscience*, 9(2), 89-91.
- [78] Van Loon, A. F., Stahl, K., Di Baldassarre, G., Clark, J., Rangecroft, S., Wanders, N., ... & Van Lanen, H. A. (2016b). Drought in a human-modified world: reframing drought definitions, understanding, and analysis approaches. *Hydrology and Earth System Sciences*, 20(9), 3631-3650.

- [79] Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate*, 23(7), 1696–1718. <https://doi.org/10.1175/2009JCLI2909.1>
- [80] Vicente-Serrano, S. M., Van der Schrier, G., Beguería, S., Azorin-Molina, C., & Lopez-Moreno, J. I. (2015). Contribution of precipitation and reference evapotranspiration to drought indices under different climates. *Journal of Hydrology*, 526, 42–54. <https://doi.org/10.1016/j.jhydrol.2014.11.025>
- [81] Vicente-Serrano, S. M., Domínguez-Castro, F., McVicar, T. R., Tomas-Burguera, M., Peña-Gallardo, M., Noguera, I., ... & El Kenawy, A. (2020a). Global characterization of hydrological and meteorological droughts under future climate change: The importance of timescales, vegetation- CO₂ feedbacks and changes to distribution functions. *International Journal of Climatology*, (5), 2557-2567.
- [82] Vicente-Serrano, S. M., McVicar, T. R., Miralles, D. G., Yang, Y., & Tomas-Burguera, M. (2020b). Unraveling the influence of atmospheric evaporative demand on drought and its response to climate change. *Wiley Interdisciplinary Reviews: Climate Change*, 11(2), e632.
- [83] Vicente-Serrano, S. M., Miralles, D. G., McDowell, N., Brodribb, T., Domínguez-Castro, F., Leung, R., & Koppa, A. (2022a). The uncertain role of rising atmospheric CO₂ on global plant transpiration. *Earth-Science Reviews*, 230(February), 104055. <https://doi.org/10.1016/j.earscirev.2022.104055>
- [84] Vicente-Serrano, S. M., Peña-Angulo, D., Beguería, S., Domínguez-Castro, F., Tomás-Burguera, M., Noguera, I., Gimeno-Sotelo, L., & El Kenawy, A. (2022b). Global drought trends and future projections. *Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences*, 380(2238), 20210285. <https://doi.org/10.1098/rsta.2021.0285>
- [85] Villani, L., Castelli, G., Yimer, E. A., Chawanda, C. J., Nkwasa, A., Van Schaeybroeck, B., ... & Bresci, E. (2024). Impacts of climate change and vegetation response on future aridity in a Mediterranean catchment. *Agricultural Water Management*, 299, 108878.
- [86] Vremec, M., Collenteur, R. A., & Birk, S. (2024). PyEt v1. 3.1: a Python package for the estimation of potential evapotranspiration. *Geoscientific Model Development*, 17(18), 7083-7103.
- [87] Wang, T., & Sun, F. (2023). Socioeconomic exposure to drought under climate warming and globalization: The importance of vegetation- CO₂ feedback. *International Journal of Climatology*, 43(12), 5778-5796.
- [88] Wang, Z., Yang, Y., Zhang, C., Guo, H., & Hou, Y. (2022a). Historical and future Palmer Drought Severity Index with improved hydrological modeling. *Journal of Hydrology*, 610, 127941.
- [89] Wang, Z., Wang, C., & Liu, S. (2022b). Elevated CO₂ alleviates adverse effects of drought on plant water relations and photosynthesis: a global meta-analysis. *Journal of Ecology*, 110(12), 2836-2849.
- [90] Wilkening, J. V., Feng, X., Dawson, T. E., & Thompson, S. E. (2024). Different roads, same destination: the shared future of plant ecophysiology and ecohydrology. *Plant, Cell & Environment*, 47(9), 3447-3465.
- [91] Xu, F., Qu, Y., Bento, V. A., Song, H., Qiu, J., Qi, J., ... & Wang, Q. (2024). Understanding climate change impacts on drought in China over the 21st century: a multi-model assessment from CMIP6. *npj Climate and Atmospheric Science*, 7(1), 32.
- [92] Yang, Y., Roderick, M. L., Zhang, S., McVicar, T. R., & Donohue, R. J. (2019). Hydrologic implications of vegetation response to elevated CO₂ in climate projections. *Nature Climate Change*, 9(1), 44–48. <https://doi.org/10.1038/s41558-018-0361-0>
- [93] Yang, Y., Zhang, S., Roderick, M. L., McVicar, T. R., Yang, D., Liu, W., & Li, X. (2020). Comparing Palmer Drought Severity Index drought assessments using the traditional offline approach with direct climate model outputs. *Hydrology and Earth System Sciences*, 24(6), 2921-2930.
- [94] Yang, Y., Roderick, M. L., Guo, H., Miralles, D. G., Zhang, L., Fatichi, S., ... & Yang, D. (2023). Evapotranspiration on a greening Earth. *Nature Reviews Earth & Environment*, 4(9), 626-641.
- [95] Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, 19(NA), 333-349.
- [96] Zeng, Z., Wu, W., Li, Y., Huang, C., Zhang, X., Peñuelas, J., ... & Ge, Q. (2023). Increasing meteorological drought under climate change reduces terrestrial ecosystem productivity and carbon storage. *One Earth*, 6(10), 1326-1339.
- [97] Zhang, X., Zhang, Y., Tian, J., Ma, N., & Wang, Y. P. (2022). CO₂ fertilization is spatially distinct from stomatal conductance reduction in controlling ecosystem water-use efficiency increase. *Environmental Research Letters*, 17(5), 054048.
- [98] Zhao, T., & Dai, A. (2015). The magnitude and causes of global drought changes in the twenty-first century under a low-moderate emissions scenario. *Journal of climate*, 28(11), 4490-4512.
- [99] Zhao, T., & Dai, A. (2022). CMIP6 model-projected hydroclimatic and drought changes and their causes in the twenty-first century. *Journal of Climate*, 35(3), 897-921.
- [100] Zhou, S. X., Prentice, I. C., & Medlyn, B. E. (2019). Bridging drought experiment and modeling: representing the differential sensitivities of leaf gas exchange to drought. *Frontiers in Plant Science*, 9, 1965.