



# Improving the representation of drought-induced tree mortality in LPJmL-5

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**Abstract.** Dynamic global vegetation models (DGVMs) are widely used to assess the impacts of climate change on forests, but their projections of future forest dynamics remain uncertain. A key source of this uncertainty is the representation of tree mortality, particularly under drought conditions. Improving drought-related mortality schemes in DGVMs is therefore essential for more reliable projections of future forest dynamics. To address this, we extended the DGVM LPJmL-5 by implementing a new drought-induced mortality formulation based on water stress, vapour pressure deficit, and phenology. This scheme introduces two Plant Functional Type (PFT)-specific parameters,  $\alpha$  and  $\beta$ , which control the onset and severity of drought-induced tree mortality. These parameters were calibrated using a multi-objective optimisation approach that considered both observed drought–mortality and drought-Gross Primary Production (GPP) relationships. We find that the new formulation improves the simulated drought–mortality relationship compared to the baseline model, particularly for tropical and temperate PFTs. While large-scale mean GPP and latent heat fluxes remain largely unchanged, the new scheme leads to stronger drought responses and impacts in several regions and reduces the strong post-drought recovery in GPP found in the baseline formulation of LPJmL-5. Overall, the results show that this relatively simple drought mortality formulation improves the representation of drought-induced mortality responses in LPJmL-5 while maintaining realistic large-scale carbon and water fluxes. Including drought-induced mortality therefore represents an important step towards more realistic simulations of vegetation responses to increasing drought stress under future climate change.



## 1 Introduction

Dynamic global vegetation models (DGVMs) are widely used to assess the impacts of climate change on forests (Higgins and Scheiter, 2012; Bonan et al., 2003; Cramer et al., 2001; Sitch et al., 2008; Li et al., 2019; Bugmann et al., 2019), but their projections of future forest dynamics remain uncertain (Li et al., 2019; Bonan et al., 2003; Cramer et al., 2001; Sitch et al., 2008). One important source of this uncertainty is the representation of tree mortality (Bugmann et al., 2019; Bircher et al., 2015; Manusch et al., 2012), particularly under drought conditions (Yao et al., 2022). While processes related to tree growth are often modelled in considerable detail, mortality is typically represented using much simpler approaches (Yu et al., 2022; Bugmann et al., 2019; Bugmann and Seidl, 2022; Fischer et al., 2025; Manusch et al., 2012). This simplification becomes particularly problematic during droughts, where mortality strongly influences forest carbon dynamics (Reichstein et al., 2013). The die-off of vegetation affects the water, carbon and nitrogen cycles as well as the vegetation cover and is thus an impactful extreme event for many vegetated regions. At the same time droughts are projected to become more frequent and intense in many regions around the world (Trenberth et al., 2014; Spinoni et al., 2018; van der Wiel et al., 2023; Wanders et al., 2015), highlighting the need for more realistic representations of mortality processes in DGVMs.

During drought, tree mortality is often linked to two key physiological mechanisms: hydraulic failure and carbon starvation (Hajek et al., 2020). Hydraulic failure occurs when water stress leads to the formation of air bubbles in the xylem, blocking water transport within the tree (Vilagrosa et al., 2012). Carbon starvation occurs when stomata remain closed for extended periods, reducing photosynthesis and limiting the tree's ability to refill its carbohydrate reserves. When carbon becomes insufficient, essential processes such as growth, maintenance, and repair are affected (Fischer et al., 2025). During drought, trees can therefore starve (carbon starvation) or die of thirst (hydraulic failure) (Fischer et al., 2025). Both mechanisms reduce productivity and can ultimately lead to tree mortality (Hajek et al., 2020), with hydraulic failure identified as one of the most important source of mortality during drought events (Choat et al., 2018; Arend et al., 2021). However, tree mortality in most DGVMs is still only represented as a function of growth efficiency and maximum age (Manusch et al., 2012; Bugmann et al., 2019). While these mortality functions capture some aspects of stress, they do not explicitly represent important drought-related mortality processes such as carbon starvation or hydraulic failure.

Because these drought-induced mortality processes are not explicitly represented in many DGVMs, models often simulate only small increases in mortality during drought years compared to non-drought years (Fischer et al., 2025). As a result, they can produce unrealistically stable biomass and, in some cases, overestimate net primary productivity during drought events (Wang et al., 2012b). Simplified mortality approaches may be sufficient in non-drought years, but they often fail to reproduce observed responses during drought events (Fischer et al., 2025). For example, the severe Central European droughts between 2018 and 2020 caused unprecedented tree mortality that DGVMs were generally unable to reproduce (Anders et al., 2025). Consequently, the inaccurate representation of drought-related tree mortality is considered one of the major shortcomings of current DGVMs (Trugman, 2022).

In addition, growth-efficiency-based mortality does not always capture differences in drought vulnerability among tree Plant Functional Types (PFTs). In particular, shade-tolerant tree PFTs may survive under low growth conditions, but this does



50 not necessarily imply greater resistance to severe drought stress (Fischer et al., 2025). Together, these limitations indicate  
that growth-based mortality alone is not sufficiently sensitive to reproduce the observed impacts of drought across different  
vegetation types.

Improving the representation of drought-related mortality in DGVMs is therefore essential for more reliable projections  
of forest dynamics under climate change. To address this research gap, we extend the widely used DGVM LPJmL-5 (von  
55 Bloh et al., 2018) by introducing a drought-related mortality formulation. LPJmL-5 has been used to simulate vegetation un-  
der historical and future climate conditions (von Bloh et al., 2018; Gerten et al., 2013; Müller and Robertson, 2014) and has  
been extensively evaluated (Schaphoff et al., 2018b, a; von Bloh et al., 2018). However, although the model includes sev-  
eral mortality processes, including growth-efficiency-based mortality, competition-induced mortality, heat stress mortality, and  
fire-induced mortality, it does not explicitly represent drought-induced mortality mechanisms such as hydraulic failure. Conse-  
60 quently, drought impacts on vegetation may be underestimated. This limitation is particularly relevant for prolonged droughts,  
where a recent evaluation of LPJmL-5 showed an overly strong recovery of simulated vegetation compared to remotely sensed  
observations (Ruijsch et al., 2026). This is likely linked to simplified representations of vegetation stress and mortality, leading  
to insufficient vegetation die-off and rapid post-drought recovery.

These limitations suggest that a better representation of drought-related mortality processes in LPJmL-5 is needed to capture  
65 vegetation responses to drought more realistically. In this study, we introduce an explicit drought-induced mortality formu-  
lation based on water stress, atmospheric demand, and phenological activity. We evaluate whether this formulation produces  
drought–mortality relationships closer to observations and assess its effects on vegetation productivity and large-scale carbon  
and water fluxes.



## 2 Methods

### 2.1 Baseline model processes

This section describes the main vegetation processes in LPJmL-5 that are relevant for this study. We focus particularly on mortality and Gross Primary Production (GPP), as both strongly influence vegetation responses to drought and are used to evaluate model performance. First, we provide an overview of the mortality processes included in the baseline model, followed by a description of how GPP is calculated and affected by environmental conditions such as drought.

#### 2.1.1 Dynamic global vegetation modelling using LPJmL-5

Vegetation dynamics were simulated with LPJmL-5 (v5.10.1; von Bloh et al. (2018)), a dynamic global vegetation model that represents natural and managed vegetation through coupled carbon, nitrogen, water, and energy fluxes (Schaphoff et al., 2018b; von Bloh et al., 2018). Simulations were performed at 0.1° spatial resolution using daily W5E5 meteorological forcing (Lange et al., 2022). Land use, land cover, soil properties, nitrogen deposition, and atmospheric CO<sub>2</sub> concentrations were prescribed from observational datasets. The model forcing and input datasets were identical to those described by Ruijsch et al. (2026). A complete overview of all forcing and evaluation datasets can be found in Appendix A.

#### 2.1.2 Mortality in LPJmL-5

In LPJmL-5, tree mortality is represented through several processes, including background (growth-efficiency) mortality, competition-induced mortality, heat stress mortality, and fire-induced mortality (Schaphoff et al., 2018b). Mortality reduces the number of individuals per unit area on an annual time step, with biomass from dead individuals being transferred to litter pools. Grasses and crops are not affected by the mortality processes in LPJmL-5. The following descriptions of the mortality processes are based on Schaphoff et al. (2018b). Figure 1 shows a conceptual framework of vegetation mortality processes in LPJmL-5. It is important to note that LPJmL-5 does not explicitly represent individual trees. Instead, each tree PFT within a grid cell is represented by a single average tree, which is scaled by the population density (*nind*). As a result, all trees of the same PFT are assumed to respond in the same way to drought. This means that differences in mortality between younger and older trees, or between smaller and larger trees, are not represented in the model.

#### Background mortality

Background mortality in LPJmL-5 depends on the growth efficiency (*gref*), defined as the ratio of net biomass increment per individual to leaf area per individual:

$$gref = \frac{bm_{delta}}{C_{leaf,ind} \cdot SLA}, \quad (1)$$



where  $C_{leaf,ind}$  is the leaf carbon per individual and  $SLA$  is the specific leaf area. The net biomass increment per individual ( $bm_{delta}$ ) is calculated as

$$bm_{delta} = \frac{bm_{inc}}{nind} - turnover_{ind}, \quad (2)$$

100 with  $bm_{inc}$  the total annual biomass increment per unit area,  $nind$  the number of individuals per unit area, and  $turnover_{ind}$  the biomass lost per individual due to turnover.

The background mortality rate is then calculated as

$$mort_{greff} = \frac{k_{mort1}}{1 + k_{mort2} \cdot greff}, \quad (3)$$

where  $mort_{greff}$  is the annual fractional mortality rate,  $k_{mort1}$  defines the maximum mortality rate, and  $k_{mort2}$  controls  
 105 the sensitivity of mortality to growth efficiency. In LPJmL-5,  $k_{mort1}$  is set to 0.03 for natural tree PFTs, corresponding to a maximum annual mortality of 3%  $yr^{-1}$ , while  $k_{mort2}$  is fixed at 0.2.

The number of individuals killed due to this background mortality is given by

$$nind_{kill} = nind \cdot mort_{greff}, \quad (4)$$

where  $nind$  is the population density (number of individuals  $m^{-2}$ ). This formulation results in a mortality rate that is not  
 110 explicitly age- or size-structured. The resulting reduction in population density then influences competition, growth, and Fractional Plant Cover (FPC) of the remaining trees, while biomass and nitrogen from dead individuals is transferred to the litter pools.

### Competition-induced mortality

115 Competition-induced mortality occurs when tree growth leads to too high tree densities, such that the summed FPC of all tree PFTs exceeds 95%. In this case, the densities of all tree PFTs are reduced proportionally to their expansion rates until the total tree FPC falls below this threshold. Herbaceous PFTs are outcompeted by expanding trees until the tree FPC reaches its maximum value of 95%, while remaining herbaceous competition is resolved through light competition.

### 120 Heat stress mortality

LPJmL-5 also includes a heat stress mortality component that applies only to boreal tree PFTs. When daily temperatures exceed a PFT-specific threshold, exceedances are accumulated over the year as growing degree days above the threshold ( $gdd_{tw}$ ). Heat stress mortality is calculated as an annual fractional rate:

$$mort_{heat} = \frac{gdd_{tw}}{tw_{PFT}}, \quad (5)$$

125 where  $tw_{PFT}$  controls the sensitivity of mortality to heat stress and is set to 400. If the calculated fraction exceeds 1, it is capped at 1, ensuring that the annual mortality fraction does not exceed 100%. The number of individuals killed due to heat stress is then calculated as

$$nind_{kill} = nind \cdot mort_{heat}, \quad (6)$$



130

### Fire-induced mortality

Fire-induced mortality is simulated using the Glob-FIRM module. Fire occurrence is determined by an exponential probability function dependent on soil moisture in the upper 50 cm and a fuel load threshold. The cumulative daily probability defines the length of the fire season, and burnt area increases non-linearly with increasing fire season length. Within burnt areas, tree mortality depends on a PFT-specific fire resistance parameter for woody plants, while all live grasses and litter are assumed to be consumed by fire. Glob-FIRM does not explicitly model ignition sources and assumes a fixed relationship between fire season length and burnt area.

### 2.1.3 GPP and drought responses

In LPJmL-5, GPP is first calculated based on the light-limited (JE) and Rubisco-limited (JC) photosynthetic rates, together with Absorbed Photosynthetically Active Radiation (APAR; Schaphoff et al. (2018b)). This represents photosynthesis under optimal conditions before environmental constraints are applied. One of the main constraints is water availability, while temperature and light availability play a less dominant role. When water supply from the soil is insufficient to meet atmospheric demand, plants experience water stress, which reduces stomatal conductance and consequently photosynthesis. This balance is represented by the water stress scalar (*wscal*), which ranges from 0 (severe water stress) to 1 (no water limitation).

Drought can also reduce productivity indirectly through its effects on phenology. In LPJmL-5, phenology determines the fraction of the active canopy, ranging from 0 (no active canopy) to 1 (fully active canopy). A decline in phenology reduces leaf area and the amount of absorbed radiation, which subsequently lowers GPP. Phenology is influenced by four limiting factors: cold temperature, light availability, water availability, and heat stress (Forkel et al., 2014; Schaphoff et al., 2018b). Each factor ranges between 0 (full limitation) and 1 (no limitation), and their combined effect determines overall canopy activity. These factors follow logistic response curves and include a memory term, allowing vegetation to respond gradually to changing environmental conditions.

LPJmL-5 uses a big-leaf approach, where all leaves of a PFT within a grid cell are represented as a single canopy with average physiological properties. As a result, drought affects GPP through changes in canopy, water stress and phenology, rather than through the response of individual trees.

## 2.2 Model modifications

The existing mortality mechanisms in LPJmL-5, including background, competition-induced, heat stress, and fire-induced mortality, do not explicitly represent drought-specific mortality processes such as hydraulic failure and carbon starvation. Background (growth-efficiency) mortality can be interpreted as a proxy for carbon starvation, reducing the number of trees when growth efficiency is low. However, hydraulic failure is not explicitly represented, even though studies suggest it can be as important as carbon starvation, if not more, during drought events (Choat et al., 2018; Arend et al., 2021).



## Mortality in LPJmL-5

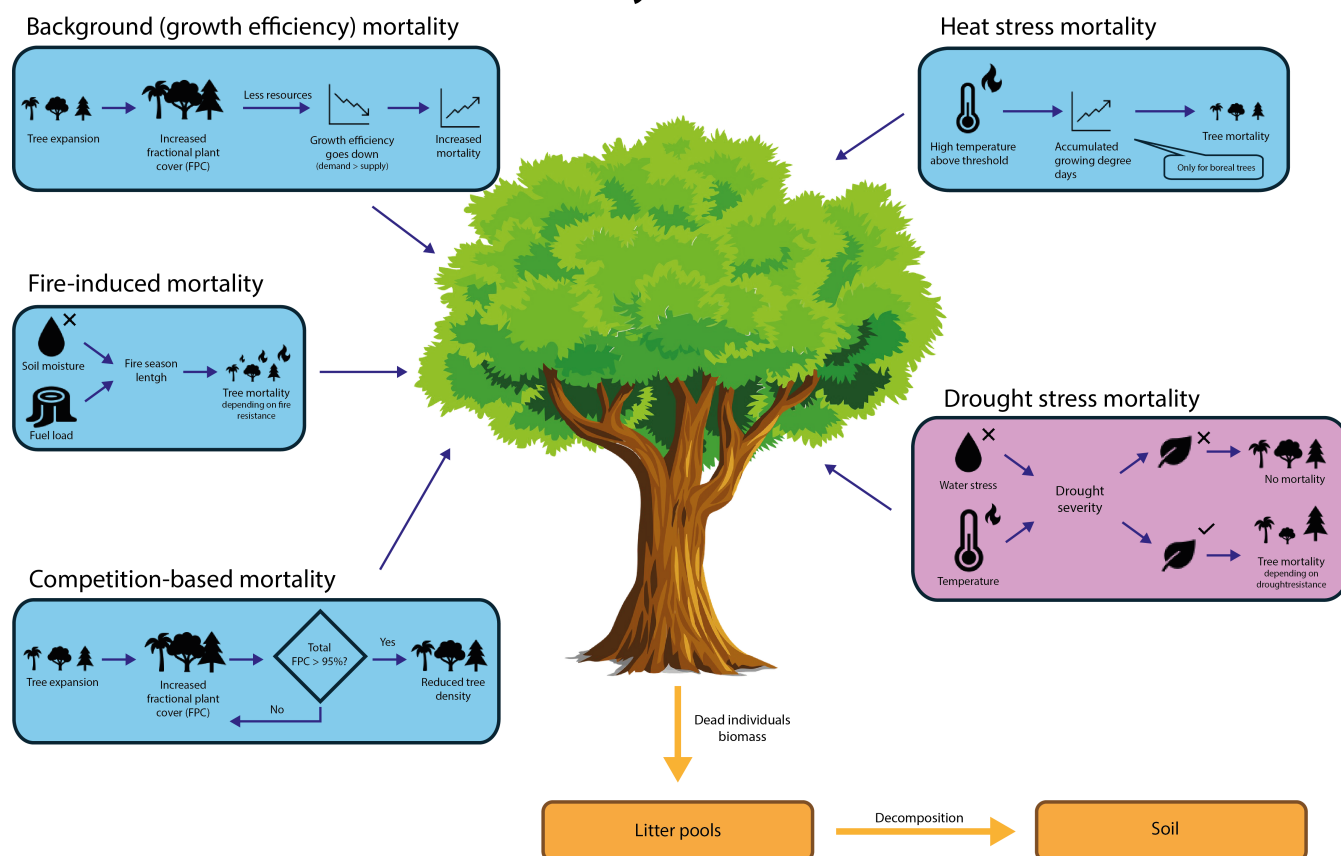


**Figure 1.** Conceptual framework of vegetation mortality processes in LPJmL-5. Tree mortality consists of four main components: (1) Background mortality, driven by growth efficiency; (2) Fire-induced mortality, determined by fuel load and soil moisture; (3) Competition-based mortality, triggered when total FPC exceeds 0.95; and (4) Heat stress mortality, affecting boreal trees via accumulated days above a certain threshold. In this study, we add the fifth mortality component: Drought stress mortality. This is calculated as a function water stress, atmospheric demand, and phenology. Dead biomass from all mortality processes is transferred to litter and soil pools.

To address this, we introduce a drought-induced mortality term that acts independently of carbon balance and is intended to capture the effects of prolonged water stress. Drought mortality is calculated on a monthly timescale so that seasonal changes in water stress directly affect the simulated vegetation, rather than being delayed or masked by annual calculations. The following subsections describe these modifications and the implementation of the new drought-induced mortality formulation.



### 165 2.2.1 Monthly background and heat stress mortality

Before implementing the new monthly drought-induced mortality, it is necessary to convert the existing background (growth-efficiency) and heat stress mortalities from annual to monthly timescales to ensure consistency with the drought mortality formulation and allows mortality responses to more directly influence PFT biomass.

We keep the original annual calculation, but distribute the annual mortality over the months of the following year. This prevents all mortality from being applied on the first day of the year and results in a more gradual reduction in population density. The monthly fractions for background and heat stress mortality are calculated as follows:

$$\begin{aligned} mort_{background,monthly} &= 1.0 - (1.0 - mort_{background,annual})^{1/12}, \\ mort_{heat,monthly} &= 1.0 - (1.0 - mort_{heat,annual})^{1/12}, \end{aligned} \quad (7)$$

which preserves the total annual heat and background mortality rates.

The approach used here allows drought-induced mortality to be calculated at a monthly timescale while keeping the model comparable to the baseline version. Tests with the Monthly Mortality (MM) configuration show that annual results remain largely unchanged (see Supplementary Materials Section S1). Fire-induced mortality was left unchanged and continues to be applied on its original annual timescale.

### 2.2.2 Drought-induced mortality

Because the existing mortality formulation does not directly account for the effects of water stress on mortality, we introduce an additional drought-induced mortality term that acts independently of the carbon balance. Drought mortality is applied on a monthly timescale, allowing seasonal variations in water availability to be reflected in mortality rates. It complements the existing background and heat stress mortality components.

Drought mortality is calculated using existing model variables that describe plant water stress, together with an additional input for atmospheric demand:

$$185 \quad mort_{drought} = phen \cdot (\alpha - wscal) \cdot VPD \cdot \beta, \quad (8)$$

where *phen* represents phenology and ensures that drought mortality only occurs during periods when leaves are present and transpiration can occur, excluding dormant periods such as winter. The term  $(\alpha - wscal)$  quantifies the water deficit, where *wscal* is the water stress scalar defined as the ratio of actual transpiration to atmospheric demand. This water stress scalar ranges from 0 (severe water stress) to 1 (no water stress), and  $\alpha$  defines the PFT-dependent threshold below which water stress leads to mortality (Figure 2), representing the level of water stress a tree can tolerate before mortality occurs. When  $wscal > \alpha$ , the term  $(\alpha - wscal)$  becomes negative, and drought-induced mortality is set to zero. Higher  $\alpha$  values indicate greater drought sensitivity, while lower values indicate higher drought tolerance. Vapour pressure deficit (*VPD*) describes atmospheric dryness and is included as an additional input dataset. Higher *VPD* increases transpirational water loss when stomata are open, intensifying plant water stress and thus contributing to drought-induced mortality. The parameter  $\beta$  represents



195 the overall sensitivity of a tree to drought and determines how strongly mortality increases once water stress exceeds the  $\alpha$  threshold. To prevent unrealistically high mortality during extreme drought conditions, drought-induced mortality is limited to a maximum of 25% per month.

The drought-induced mortality rate is calculated on a daily timestep and aggregated to monthly values by averaging the daily mortality rates over the month. This allows short-term fluctuations in water stress and atmospheric demand to be included  
 200 in the mortality calculation, while avoiding unrealistically high mortality from single day extreme dry events. As a result, the drought-induced mortality (DM) model will reflect prolonged drought stress rather than stress caused by very short-term drought events.

At the end of each month, the resulting drought-induced mortality rate is applied to the population density of each tree PFT. The number of individuals killed due to drought is calculated as

$$205 \quad n_{ind_{kill,drought}} = n_{ind} \cdot mort_{drought}. \quad (9)$$

The biomass and nitrogen from the dead individuals is then transferred to the corresponding litter pools, as with the other mortality processes in LPJmL-5.

### 2.3 Calibration of PFT specific parameters $\alpha$ and $\beta$

The drought mortality formulation introduces two PFT-specific parameters ( $\alpha$  and  $\beta$ ), which were calibrated using the multi-  
 210 objective optimization framework Optuna (Akiba et al., 2019). The optimization aims to find the parameter combination that best reproduces the observed drought responses in tree mortality and GPP. This is done by minimizing a set of objective functions, which measure how closely the simulated drought responses match the observations. For each trial, Optuna tests a different combination of  $\alpha$  and  $\beta$  and evaluates the resulting model performance. Separate mortality and GPP objectives were defined for each tree PFT, resulting in a total of 16 objectives.

#### 215 2.3.1 Mortality and GPP objective functions

The mortality objective is based on the results of Greenwood et al. (2017), who showed that log-transformed annual tree mortality increases by 0.46 (95% CI: 0.2–0.7) for each unit decrease in the Standardized Precipitation Evapotranspiration Index (SPEI). No significant differences in drought-mortality sensitivity were found between forest types or leaf types. Based on this relationship, the first calibration objective is to match the simulated  $\log_{10}(\text{annual mortality})$ -SPEI slope to the observed  
 220 relationship across all PFTs. The intercept of this observed relationship is fixed at -1.96, corresponding to a median annual mortality rate of 1.1% per year (Idoate-Lacasia et al., 2025).

To ensure that realistic mortality responses do not come at the expense of unrealistic productivity responses, a second calibration objective is included based on the sensitivity of GPP to drought. This sensitivity is derived from standardized GPP anomalies from the MODIS GPP product (Didan, 2015a, b) as a function of SPEI-12 (Ruijsch et al., 2026), both regridded  
 225 to a monthly temporal and 0.1° spatial resolution (Appendix A). Only water-limited regions, where evaporative demand exceeds precipitation ( $P/PET < 1$ ), are considered, as vegetation in energy-limited regions may show neutral or even positive

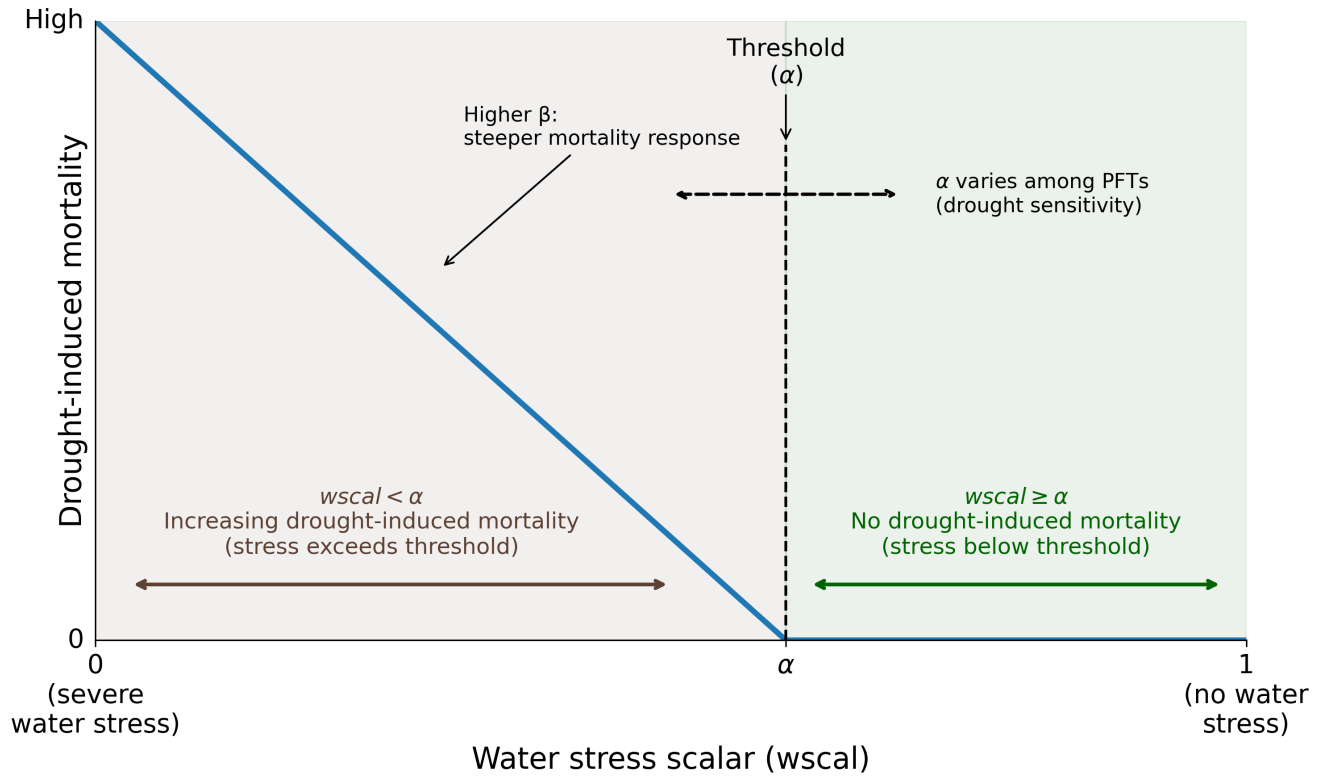


**Figure 2.** Schematic illustrating the water stress scalar ( $wscal$ ) and the parameters  $\alpha$  and  $\beta$  used in Equation 8. When  $wscal \geq \alpha$ , no drought-induced tree mortality occurs. When  $wscal < \alpha$ , mortality increases with increasing water stress. The parameter  $\beta$  controls the steepness of this response.

responses to drought (Ruijsch et al., 2025). MODIS land-cover classes are mapped to dominant LPJmL-5 PFTs following Ruijsch et al. (2026), and only grid cells with at least 80% dominance of a single land-cover type are included. The GPP objective is based on the relationship between standardized GPP anomalies and SPEI-12, with an intercept fixed at 0.0, representing long-term average conditions. The target slopes and intercepts for both objective functions can be found in Table B1.

For each optimization trial, a linear regression was fitted to the simulated mortality and GPP responses and compared to the corresponding objective function. For mortality and GPP, linear regressions were fitted between  $\log_{10}(\text{annual mortality})$  and annual mean SPEI-12, and between monthly standardized GPP/FPC anomalies and monthly SPEI-12, respectively. Simulated GPP was normalized by FPC to account for differences in vegetation cover, and PFTs with an FPC below  $10^{-5}$  were excluded. Only the period 2000-2019 was used, corresponding to the overlap between the MODIS GPP observations and the available climate forcing data. The root mean square error (RMSE) between the fitted and objective relationships was then calculated for both mortality and GPP and used as the loss values in the multi-objective optimization.

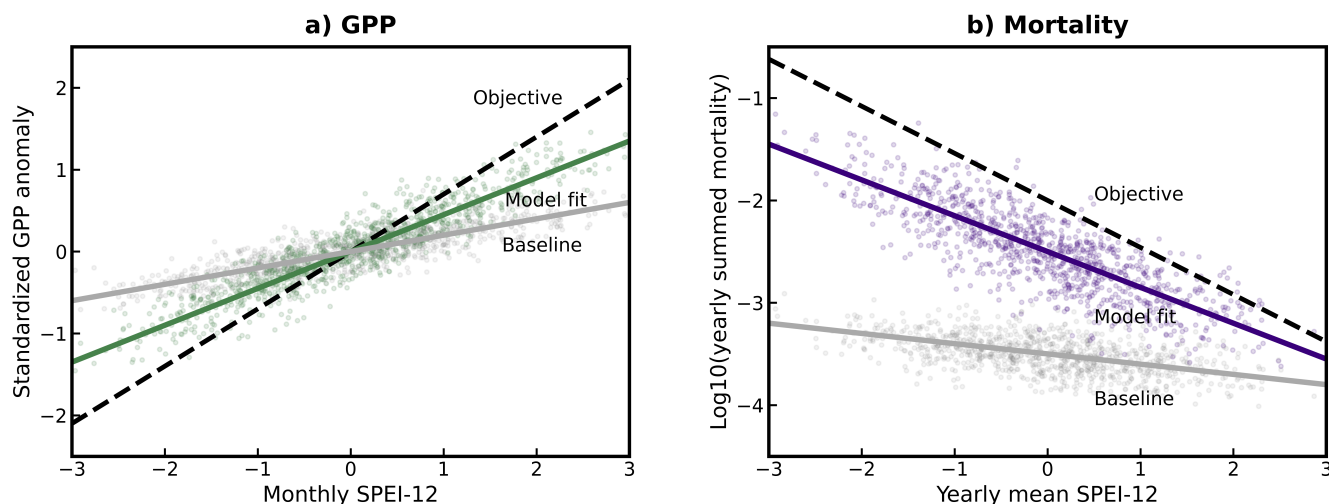


**Figure 3.** Examples of the (a) SPEI-12–GPP and (b) SPEI-12–mortality relationships used in the calibration. Grey lines indicate the baseline LPJmL-5 simulation, while green (GPP) and purple (mortality) lines show the calibrated model for a given  $\alpha$  and  $\beta$ . Dashed black lines represent the objective functions derived from MODIS GPP and Greenwood et al. (2017). The optimisation aims to find  $\alpha$  and  $\beta$  that minimise the distance between the modelled and objective lines.

### 2.3.2 Multi-objective optimization to identify the best combination of $\alpha$ and $\beta$

For each tree PFT, 100 optimization trials were performed to identify the best combination of  $\alpha$  and  $\beta$ . Running LPJmL-5 globally at  $0.1^\circ$  spatial resolution for every trial would have been computationally too expensive. Therefore, the optimization was limited to subsets of grid cells. For each PFT, ten  $8 \times 8$  blocks of grid cells were selected in water-limited regions based on the highest FPC of that PFT and were required to be at least 200 km apart (Figure B1). This resulted in 640 grid cells per PFT ( $10 \times 8 \times 8$ ) and a total of 8000 model simulations across all PFTs.

For each calibration location, a 3000-year spin-up was first performed using the baseline model configuration, followed by an additional 180-year spin-up with the Monthly Mortality (MM) formulation until 1960. The optimization trials were then run from 1960 onwards with different values of  $\alpha$  and  $\beta$ , giving FPC time to adjust to the modified mortality parameters. Sensitivity tests showed that FPC generally stabilized within approximately 20 years after changes in  $\alpha$  and  $\beta$ , providing sufficient adjustment time.

For each PFT, the mortality and GPP losses from all optimization trials were analysed using a Pareto front. The Pareto front identifies parameter combinations for which no further improvement in one objective can be achieved without worsening the other (Deb and Gupta, 2010). The final parameter combination was selected as the point closest to the origin on the Pareto front, representing the best balance between the mortality and GPP losses (see Supplementary Materials Section S2).



## 2.4 Validation and evaluation of the drought mortality function in LPJmL-5

After calibration, the optimized  $\alpha$  and  $\beta$  values for each PFT were implemented in a global LPJmL-5 simulation. Model performance was then evaluated by comparing the modified DM model with the baseline simulation in terms of both mortality and GPP responses.

### 2.4.1 Mortality validation

Direct validation of simulated tree mortality is difficult because, to our knowledge, currently no consistent global observational vegetation mortality time series exist. Instead, we evaluate whether the model reproduces the observed relationship between SPEI-12 and tree mortality. Following Greenwood et al. (2017), we analysed the relationship between annual SPEI-12 and log-transformed annual mortality for each PFT. As this study focuses on drought impacts, only conditions with SPEI-12 < 0 were included. Model performance was assessed by comparing the simulated mortality-SPEI slopes with the observed slope of  $-0.46$ . A model was considered to perform better when its mortality slope was closer to this observed relationship.

### 2.4.2 GPP and latent heat flux (LE) validation

Because mortality observations are limited, we also evaluated model performance using GPP and latent heat flux (LE), for which observational datasets are available. Site-level GPP and LE observations from FLUXNET (Pastorello et al., 2020) were compared with model simulated GPP and LE for the corresponding PFT within that grid cell for both the baseline and DM simulations.

For the model simulations, LE was derived from simulated evapotranspiration as

$$LE = \frac{ET \cdot \lambda}{\Delta t}, \quad (10)$$

where  $ET$  is monthly evapotranspiration,  $\lambda = 2.45 \times 10^6 \text{ J kg}^{-1}$  is the latent heat of vaporization, and  $\Delta t$  is the number of seconds per month, yielding latent heat flux in  $\text{W m}^{-2}$ .

Model performance was quantified using the Kling-Gupta Efficiency (KGE; Gupta et al., 2009), which combines correlation, bias, and variability into a single performance metric:

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}, \quad (11)$$

where  $r$  is the correlation between observations and simulations,  $\alpha = \frac{\sigma_{sim}}{\sigma_{obs}}$  measures differences in variability, and  $\beta = \frac{\mu_{sim}}{\mu_{obs}}$  measures bias. Here,  $\sigma_{obs}$  and  $\sigma_{sim}$  are the standard deviations of the observations and simulations, respectively, while  $\mu_{obs}$  and  $\mu_{sim}$  are the corresponding means. KGE values greater than  $-0.41$  indicate that the model performs better than using the observed mean as a benchmark, while a value of 1 indicates perfect agreement between simulations and observations (Knoben et al., 2019).



### 2.4.3 Extreme drought response evaluation

Because direct global observations of drought-induced mortality are unavailable, we additionally evaluated the response of the model under a 10-year precipitation exclusion experiment. The experiment was performed to assess whether the inclusion of drought mortality leads to increased vegetation dieback compared to the baseline model. Under these conditions, vegetation cover is expected to decline towards zero. To quantify the rate of decline, we calculated the e-folding timescale of the FPC, defined as the time required for FPC to decrease to  $1/e$  (approximately 37%) of its initial value. E-folding times were first calculated separately for each tree PFT in each grid cell. These PFT-specific values were then combined into a single map by weighting each PFT by its FPC and normalising by total tree FPC within each grid cell. Short e-folding times indicate faster vegetation decline, while longer times indicate greater resistance to drought conditions. Because this experiment has no observational benchmark, it is used here as a comparison between the baseline and DM model configurations rather than a formal validation.

### 2.5 Drought response analysis

After evaluating the model performance, we focused on the differences between the baseline and DM simulations during historical drought conditions. To evaluate these differences, we performed two drought-response analyses: (i) a temporal analysis of standardized tree GPP anomalies ( $GPP_{SA}$ ) in six focus regions, covering both normal droughts (NDs) and multi-year droughts (MYDs), and (ii) a spatial analysis of the mean response of  $GPP_{SA}$  during MYDs.

For the temporal analysis,  $GPP_{SA}$  time series were calculated for both the baseline and DM simulations using z-score normalization. MYDs were defined as periods during which SPEI-12 remained below -1 for at least 12 consecutive months, while periods with SPEI-12 below -1 lasting less than 12 months were classified as NDs. SPEI-12 was chosen because it is widely used in MYD studies (van Mourik et al., 2025; Venkataraman et al., 2016; Tarafdar and Dutta, 2023; Ruijsch et al., 2025; Češljär et al., 2024; Odongo et al., 2025), and was also used in the calibration objective function (Section 2.3.1). Previous work has shown that MYDs can substantially reduce vegetation productivity (Ruijsch et al., 2025). However, LPJmL-5 tends to underestimate these impacts and often exhibits short-term recovery spikes following brief rainfall events (Ruijsch et al., 2026). We therefore assessed whether the DM model better captures these observed drought responses compared to the baseline model setup as used by Ruijsch et al. (2026). The selected focus regions include California (CAL), the Rhine–Meuse delta in Western Europe (WEU), the Brahmaputra River basin (BRA), central Argentina (ARG), the Orange River basin in southern Africa (SA), and the Murray–Darling basin in Australia (AUS) (Appendix A). These regions correspond to those used by Ruijsch et al. (2025) and were selected based on the occurrence of MYDs, geographic and climatic diversity, and variation in vegetation types. The spatial analysis examines the response of  $GPP_{SA}$  during MYD events. We calculated the mean  $GPP_{SA}$  during MYD periods globally, for both individual tree PFTs and all tree PFTs combined.



### 3 Results

This section shows the results of the calibration and optimization of the PFT-specific drought parameters (Section 3.1), followed by the validation of the modified model (Section 3.2), an evaluation of the effects of the new drought mortality formulation on global vegetation patterns and extreme drought responses (Section 3.3), and a historical drought response analysis (Section 3.4).

#### 3.1 Calibration and multi-objective optimization of PFT-specific drought parameters

The multi-objective optimization (Section 2.3) generated a total of 100 parameter combinations for each tree PFT, resulting in a Pareto front that captures the trade-off between mortality and GPP loss. The complete set of optimization results, including all Pareto fronts, is provided in Section S2 in the Supplementary Materials. From these, the parameter set with the shortest distance to the origin was selected for the DM simulations, with the resulting  $\alpha$  and  $\beta$  values shown in Table 1. The calibrated values vary considerably among PFTs, indicating clear differences in drought sensitivity.

**Table 1.** Final calibrated drought mortality parameters ( $\alpha$  and  $\beta$ ) for each PFT, selected from the Pareto fronts and used in all subsequent Drought Mortality (DM) simulations.  $\alpha$  determines the value of  $w_{scal}$  for the onset of mortality, while  $\beta$  controls how fast mortality increases once this threshold is exceeded.

| PFT type                               | $\alpha$ | $\beta$ |
|----------------------------------------|----------|---------|
| Boreal broadleaved summergreen tree    | 0.371    | 1.535   |
| Boreal needleleaved summergreen tree   | 0.026    | 24.583  |
| Boreal needleleaved evergreen tree     | 0.026    | 3.534   |
| Temperate broadleaved summergreen tree | 0.496    | 17.755  |
| Temperate broadleaved evergreen tree   | 0.187    | 8.386   |
| Temperate needleleaved evergreen tree  | 0.111    | 22.103  |
| Tropical broadleaved evergreen tree    | 0.099    | 0.927   |
| Tropical broadleaved raingreen tree    | 0.560    | 1.465   |

To assess the performance of the calibrated parameter sets, mortality and GPP objective losses were evaluated at the calibration locations (Figure B1) for the baseline, MM, and DM configurations. Figure 4 shows the results using the parameters from Table 1. For mortality, the DM formulation reduces the objective loss for 7 out of 8 PFTs compared to the baseline and improves upon the MM formulation for all PFTs. The only PFT without a reduction in mortality objective loss compared to the baseline is boreal needleleaved evergreen trees. For GPP, the DM formulation reduces the objective loss for four PFTs, while the remaining PFTs show an increase in objective loss. For tropical broadleaved evergreen, temperate needleleaved evergreen, and temperate broadleaved summergreen trees, the increase in GPP objective loss is outweighed by a larger reduction in mortality objective loss, resulting in an overall improvement compared to the baseline model.

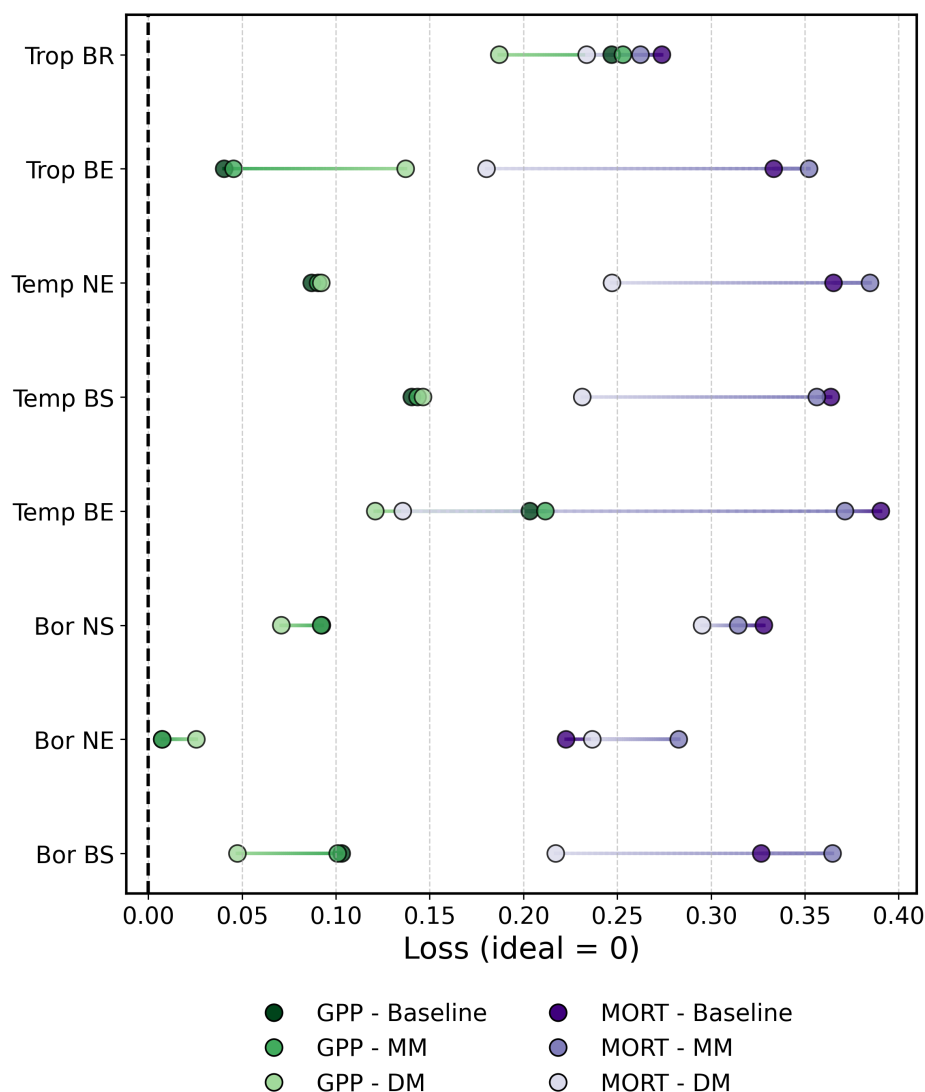


**Figure 4.** GPP (green) and mortality (purple) losses for the baseline, Monthly Mortality (MM), and calibrated Drought Mortality (DM) configurations. Lower losses indicate a closer agreement to the objective drought response. PFT abbreviations are: Trop BE (tropical broadleaved evergreen), Trop BR (tropical broadleaved raingreen), Temp NE (temperate needleleaved evergreen), Temp BE (temperate broadleaved evergreen), Temp BS (temperate broadleaved summergreen), Bor NE (boreal needleleaved evergreen), Bor BS (boreal broadleaved summergreen), and Bor NS (boreal needleleaved summergreen).

330 To better understand how the calibrated  $\alpha$  and  $\beta$  values translate into drought responses, the values from Table 1 were inserted into Equation 8 to generate the drought mortality curves shown in Figure 5. Both VPD and phenology are fixed at 1,



so differences between the curves are solely driven by  $\alpha$  and  $\beta$ . Results for varying VPD and phenology are shown in Section S3 in the Supplementary Materials.

The curves in Figure 5 show clear differences in the onset and strength of drought-induced tree mortality among PFTs. For example, tropical broadleaved evergreen and boreal needleleaved evergreen trees show a weaker drought mortality response across the full range of  $wscal$  values compared to most other PFTs. In contrast, temperate broadleaved summergreen trees begin to experience mortality at relatively high  $wscal$  values, after which mortality increases rapidly as  $wscal$  decreases further. In the remainder of this study, we use the final parameter set shown in Table 1 for all DM simulations.

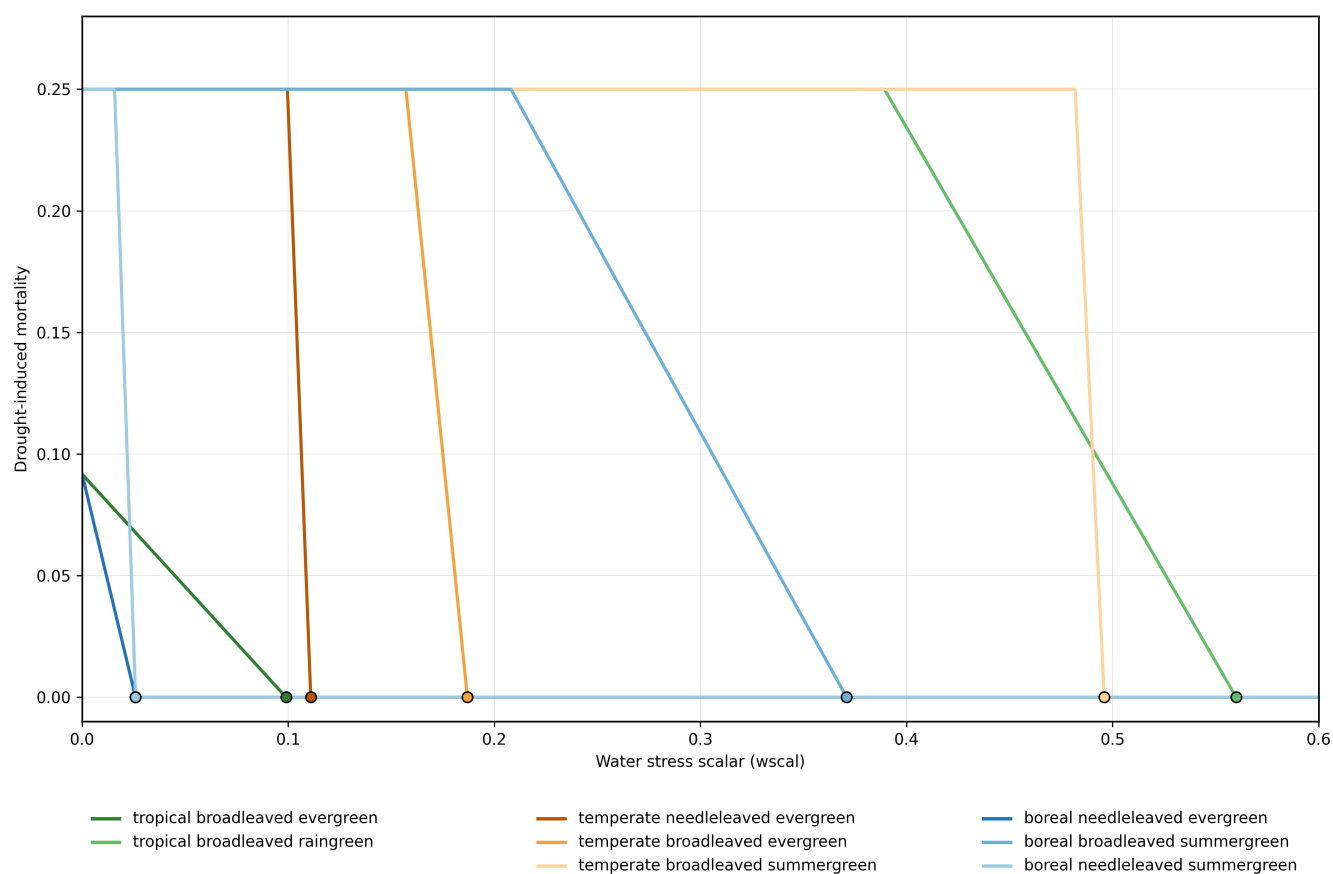


**Figure 5.** Theoretical drought mortality response as a function of the water stress scalar ( $wscal$ ) for each PFT, based on the calibrated  $\alpha$  and  $\beta$  values. Drought mortality begins when  $wscal$  falls below the PFT-specific threshold  $\alpha$ , while  $\beta$  controls how quickly mortality increases under increasing water stress. Vapour pressure deficit (VPD) and phenology are fixed at 1.



### 3.2 Validation of LPJmL-5 with the added drought mortality formulation

340 Direct validation of simulated tree mortality remains difficult because no global observational dataset of monthly tree mortality is currently available. We therefore focus on evaluating whether the model reproduces the observed relationship between drought severity and mortality. In addition, we assess model performance against observations of GPP and LE to determine whether the new drought mortality formulation affects the model's ability to reproduce carbon and water fluxes.

#### 3.2.1 Validation of the mortality response to drought

345 To evaluate the mortality response, the relationship between annual mortality and SPEI was analysed for the three model configurations (baseline, MM, and DM), considering only drought conditions ( $\text{SPEI} < 0$ ). For each configuration and PFT, mortality–SPEI slopes were calculated and compared with the observational relationship reported by Greenwood et al. (2017) (Figure 6).

The baseline model shows only a weak increase in mortality with increasing drought severity, with slopes that are generally much smaller than observed values. Switching mortality processes to a monthly timestep (MM) leads to only small changes. Although mortality slopes move closer to the observational benchmark for 4 of the 8 tree PFTs, all MM slopes remain outside the observed 95% confidence interval. In contrast, the DM simulation produces a much stronger mortality response to drought. For most temperate and tropical PFTs, the resulting slopes fall within the observational confidence interval. Boreal PFTs remain relatively insensitive to drought, consistent with the calibrated drought mortality curves shown in Figure 5.

#### 355 3.2.2 KGE validation of GPP and LE

Because direct observations of tree mortality are not available at the global scale, model performance was additionally evaluated against FLUXNET observations of GPP and LE using the KGE. Figure 7 compares KGE values for the baseline and DM simulations.

Overall, the spatial patterns of KGE are very similar between the two model configurations. For GPP, the DM simulation shows both small improvements and slight deteriorations at individual sites, but the overall differences are small (Figure 7). Most sites cluster close to the 1:1 line, suggesting that adding the drought mortality formulation has little effect on overall GPP performance. The largest differences occur at sites with already low KGE values, while sites above the benchmark threshold of -0.41 show almost no change between simulations.

Differences in LE are even smaller. KGE values for the DM and baseline simulations are nearly identical for most sites, with points closely following the 1:1 line. This suggests that the drought mortality formulation has little influence on the overall model ability to reproduce observed LE, which is expected because the new drought mortality only affects vegetation under drought stress.

Spatially, the highest KGE values are generally found in Europe and parts of North America, while lower performance occurs in tropical regions and parts of Australia. However, these broad spatial patterns are very similar between the baseline and DM simulations. Overall, the results show that the new drought mortality formulation increases the sensitivity of tree mortality to

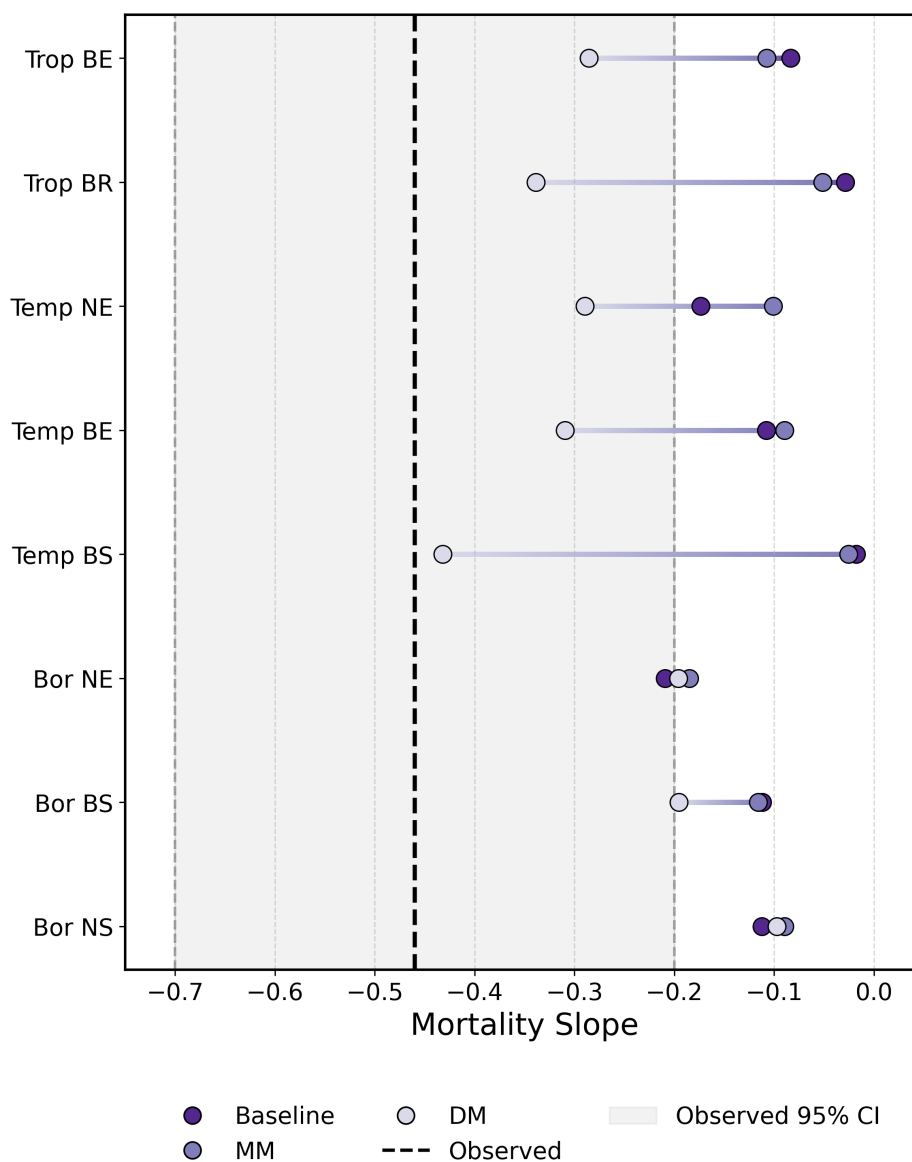


**Figure 6.** Mortality-SPEI slopes for drought conditions ( $\text{SPEI} < 0$ ) for each PFT under the baseline, Monthly Mortality (MM), and Drought Mortality (DM) model configurations. The dashed black line indicates the observed slope from Greenwood et al. (2017), while the shaded area indicates the corresponding 95% confidence interval. PFT abbreviations are: Trop BE (tropical broadleaved evergreen), Trop BR (tropical broadleaved raingreen), Temp NE (temperate needleleaved evergreen), Temp BE (temperate broadleaved evergreen), Temp BS (temperate broadleaved summergreen), Bor NE (boreal needleleaved evergreen), Bor BS (boreal broadleaved summergreen), and Bor NS (boreal needleleaved summergreen).

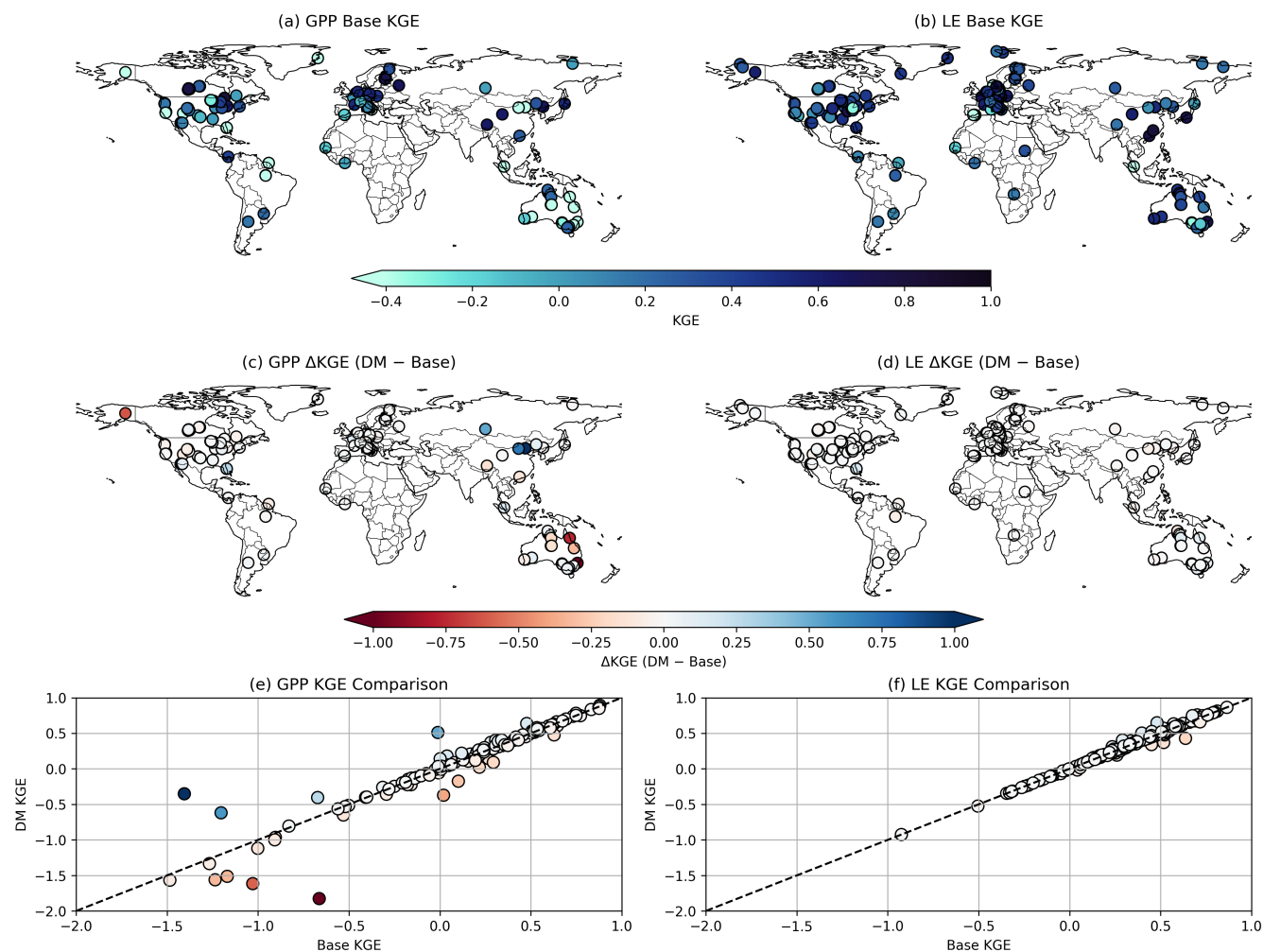


**Figure 7.** Validation of simulated GPP and LE against FLUXNET observations using the Kling-Gupta Efficiency (KGE). The first shows KGE values for the baseline simulation, the second row shows the difference between the drought-mortality (DM) and baseline simulations ( $\Delta KGE = DM - \text{Baseline}$ ), and the third row compares KGE values from both simulations. Points above the 1:1 line indicate improved performance in the DM simulation, while points below the line indicate better performance in the baseline simulation. Positive  $\Delta KGE$  values (blue) indicate improvements due to the drought mortality formulation, whereas negative values (red) indicate deterioration.

drought while largely preserving the model's ability to reproduce observed GPP and LE. This indicates that the added drought mortality primarily affects vegetation during drought conditions without substantially altering model behaviour under normal conditions.



### 3.3 Evaluation of the difference between the baseline and DM simulations

375 Having established that the drought mortality formulation improves the simulated mortality response while preserving model performance for GPP and LE, we next evaluate how the addition of drought mortality changes simulated vegetation dynamics at the global scale and under an idealized extreme drought experiment.

#### 3.3.1 Evaluation of the difference in mortality, GPP and LE

380 Next, the calibrated  $\alpha$  and  $\beta$  values were used in a global LPJmL-5 simulation to assess how the new drought mortality formulation affects global patterns of mortality, GPP and LE. Figure 8 shows the differences between the baseline and DM simulations for the period 2000–2019. Tree mortality is calculated by weighting PFT-specific mortality with the corresponding FPC and summing across all tree PFTs, resulting in the fraction of trees dying per year.

The introduction of drought mortality leads to a global increase in simulated tree mortality from  $0.7\% \text{ yr}^{-1}$  in the baseline to  $0.9\% \text{ yr}^{-1}$  in the DM simulation. The strongest increase occurs in the tropical regions, where annual mortality rates reach approximately  $7\% \text{ yr}^{-1}$  in some areas. Smaller increases are visible in temperate regions, while boreal regions show little to no change. Compared to the baseline simulation, where mortality rates are relatively uniform and generally stay between 1 and  $2\% \text{ yr}^{-1}$ , the DM simulation produces much stronger spatial variability in mortality. The weak response in boreal regions is consistent with Figure 5, which shows that boreal needleleaved PFTs are among the least sensitive to drought in the calibrated mortality formulation.

390 Despite the increase in mortality, the overall patterns of GPP and LE remain very similar between the baseline and DM simulations. This suggests that the additional drought mortality has only a limited effect on large-scale carbon uptake and evapotranspiration. A possible explanation is that the remaining vegetation can make use of resources that become available after tree mortality, resulting in relatively small changes in total fluxes.

#### 3.3.2 Evaluation of the difference in extreme drought responses

395 To evaluate whether the drought mortality formulation leads to a stronger vegetation response under extreme drought conditions, we performed a 10-year rain exclusion experiment in which precipitation was set to zero. This experiment does not represent a direct validation against observations, but provides an evaluation of whether the added drought mortality increases vegetation decline under prolonged water stress.

400 The introduction of drought mortality generally reduces e-folding times, indicating that vegetation declines faster under prolonged drought conditions in the DM simulation compared to the baseline model (Figure 9). The largest reductions are found for tropical broadleaved evergreen trees and temperate broadleaved summergreen trees, while boreal PFTs show smaller changes. Boreal needleleaved trees generally have longer e-folding times, suggesting that they survive longer under extreme drought conditions. This pattern is consistent with the calibrated drought mortality functions (Figure 5), which show that these PFTs only start experiencing mortality under relatively strong water stress. Overall, the shorter e-folding times in the

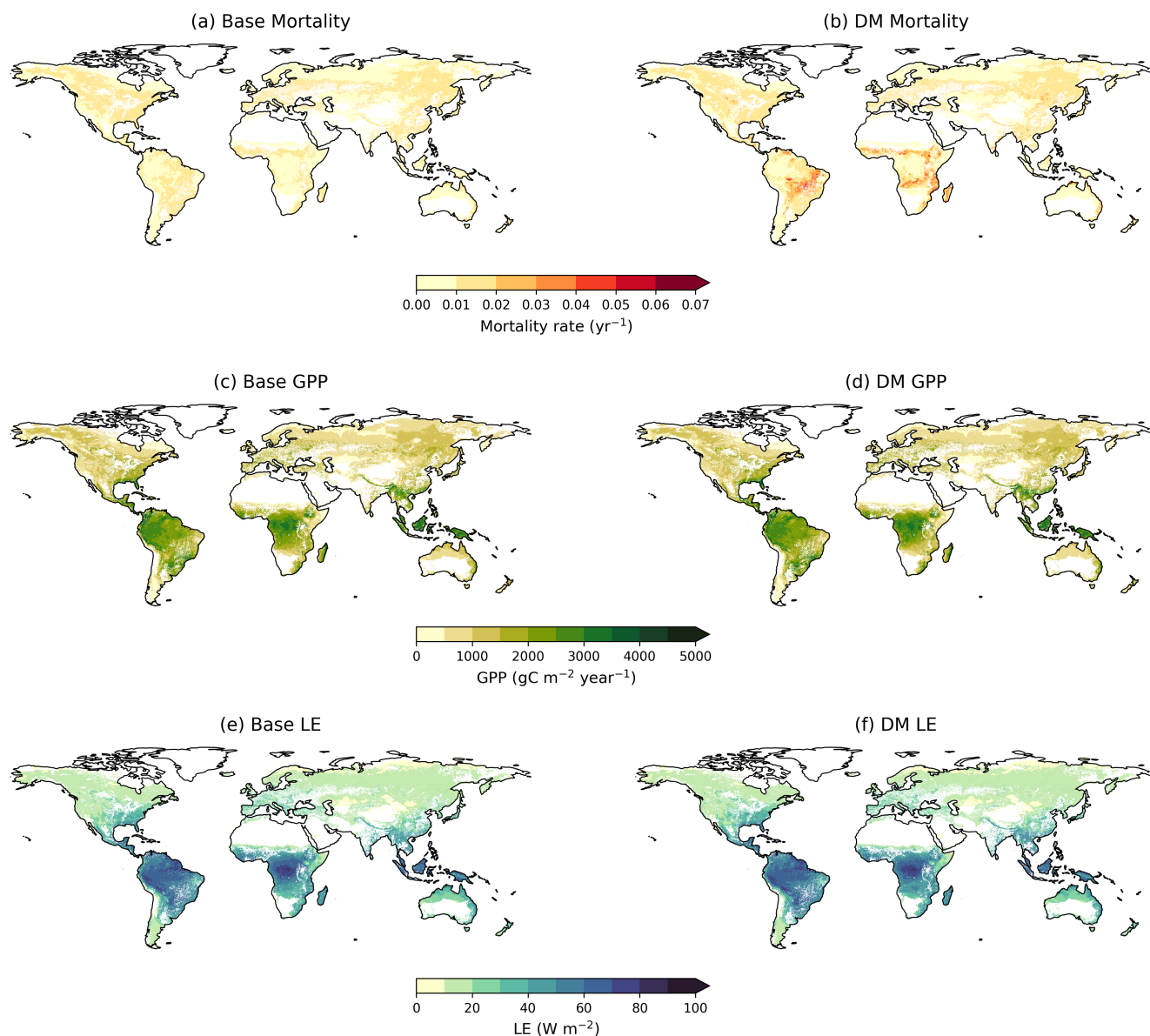
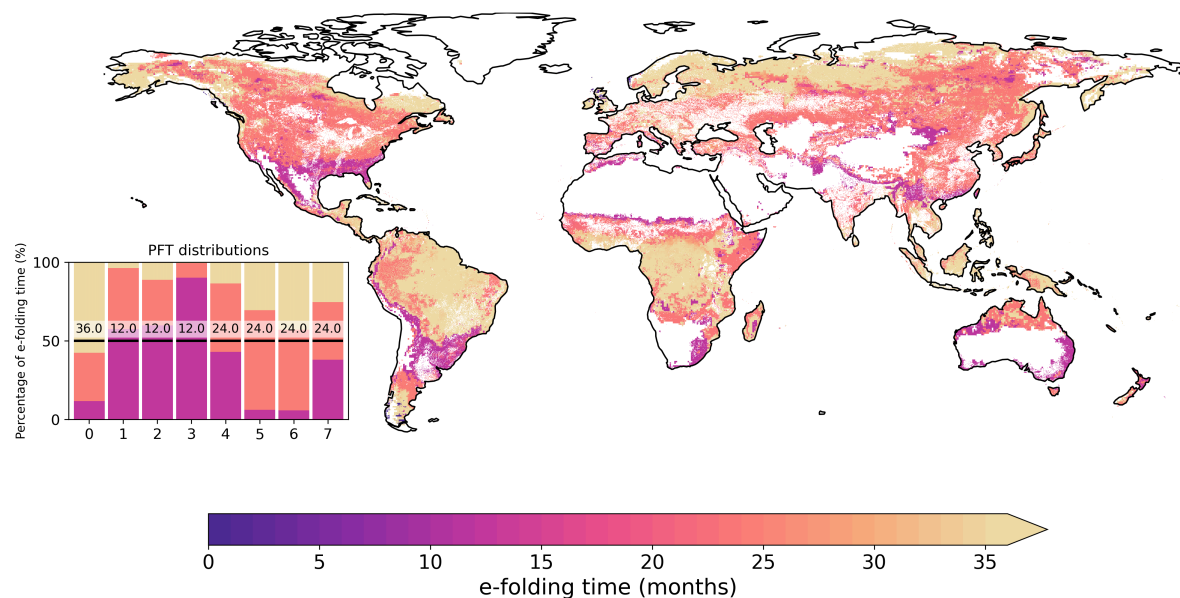


**Figure 8.** Mean annual tree mortality rate, gross primary productivity (GPP), and latent heat flux (LE) for the period 2000-2019 in the baseline and drought mortality (DM) simulations. Tree mortality was calculated by weighting PFT-specific mortality rates by their corresponding fractional plant cover (FPC) and summing across all tree PFTs. Regions without tree cover are masked.

405 DM simulation indicate that the addition of drought mortality leads to a stronger vegetation response to prolonged drought conditions.



**a) Baseline model**



**b) DM model**

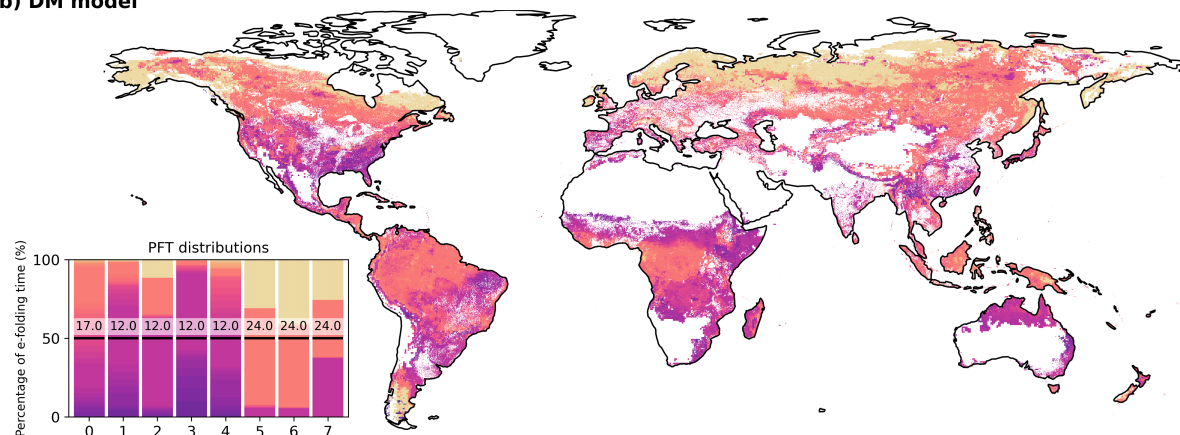


**Figure 9.** E-folding timescales of tree fractional plant cover (FPC) during the 10-year rain exclusion experiment for (a) the baseline model and (b) the drought mortality (DM) model. Lower values indicate faster vegetation decline under prolonged drought conditions. Insets show the distribution of e-folding timescales for individual tree PFTs: (0) Tropical broadleaved evergreen, (1) Tropical broadleaved raingreen, (2) Temperate needleleaved evergreen, (3) Temperate broadleaved evergreen, (4) Temperate broadleaved summergreen, (5) Boreal needleleaved evergreen, (6) Boreal broadleaved summergreen, and (7) Boreal needleleaved summergreen.



### 3.4 Drought response

The previous section evaluated whether the DM model improves agreement with available observations compared to the baseline model. Having established that the DM performs similarly to the baseline model for GPP and LE while producing a more realistic mortality response to drought, we now examine how it behaves under historic drought conditions. We first analyse regional time series of tree  $GPP_{SA}$  and mortality during drought events (Section 3.4.1). We then investigate the spatial response of tree  $GPP_{SA}$  during MYDs (Section 3.4.2).

#### 3.4.1 Time series of tree $GPP_{SA}$

To investigate drought responses, we analysed regional time series of tree  $GPP_{SA}$  and mortality for the baseline and DM models (Figure 10). Grass PFTs were excluded to isolate the tree response, as grass PFTs are not included in the new drought mortality. Total tree mortality was computed as the product of mortality rate and FPC for each tree PFT and then averaged across grid cells with non-zero tree cover within each region. Overall, the  $GPP_{SA}$  differences between the two model configurations are generally small, which is consistent with the limited differences in GPP reported in Section 3.2. However, clearer differences are visible during some specific drought events.

The largest differences are found in AUS. Here, the DM simulation shows higher mortality rates during drought periods and a weaker recovery of  $GPP_{SA}$ . This is especially clear during the 2014 and 2018 MYDs. In the baseline simulation,  $GPP_{SA}$  recovers quickly during short periods of relief within an ongoing MYD and briefly rises above one standard deviation, whereas recovery is more muted in the DM simulation. This suggests that increased drought-induced mortality reduces the ability of vegetation to quickly recover during short periods of reduced drought stress.

The other focus regions show smaller differences. In WEU, the two simulations behave almost identically, with no clear differences in either  $GPP_{SA}$  or mortality, except for the one-year shift in mortality associated with the change from the baseline to the MM configuration. CAL shows a similar pattern, with little change in both variables between the DM and baseline simulations. In BRA and ARG, slightly higher mortality is visible during some drought years, while  $GPP_{SA}$  remains largely unchanged. This suggests that reductions in tree density may be partly compensated by remaining vegetation increasing their GPP, likely due to reduced competition for resources. In SA, the DM simulation shows slightly higher mortality during drought periods and a small reduction in  $GPP_{SA}$  recovery, but differences are small.

Overall, the differences between the baseline and DM simulations vary between regions and drought events, with the largest differences occurring in AUS, while other regions show smaller changes in both  $GPP_{SA}$  and mortality.



**Figure 10.** Timeseries of  $GPP_{SA}$  and annual tree mortality for the baseline and DM models across the focus regions. Solid lines represent  $GPP_{SA}$ , while dashed lines represent mortality. MYD and ND periods are shaded in red and orange, respectively. The focus regions are: California (CAL), the Rhine river basin Western Europe (WEU), Brahmaputra (BRA), Argentina (ARG), South Africa (SA), and the Murray–Darling Basin in Australia (AUS).



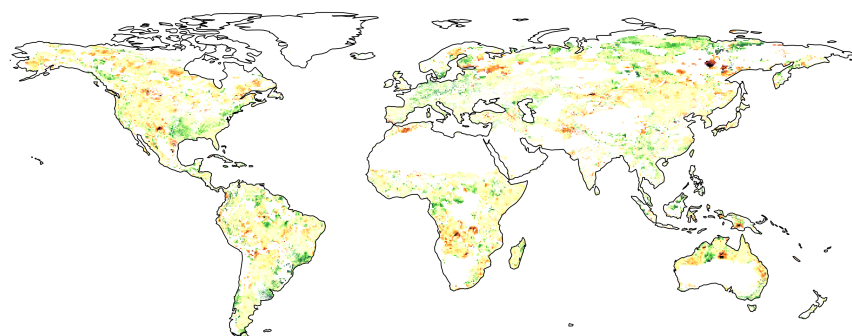
### 435 3.4.2 Response to MYDs

Building on the regional time series analysis, global patterns of  $GPP_{SA}$  during MYDs were examined to assess whether the DM model leads to stronger reductions in  $GPP_{SA}$  than the baseline model (Figure 11). Negative anomalies indicate reduced GPP relative to normal conditions, while positive anomalies indicate above-average GPP. The figure shows results for all trees combined as well as the distribution of  $GPP_{SA}$  for individual tree PFTs.

440 Spatially, the changes in mean  $GPP_{SA}$  during MYDs are limited between the two simulations. However, some regional differences do emerge. The strongest changes are found in tropical regions and parts of Australia, whereas many boreal regions remain largely unchanged. These patterns are in line with the relatively weak drought response for boreal PFTs and the higher mortality rates in tropical regions shown in Figure 8. Similar behaviour is visible in the KDE distributions. Tropical PFTs show substantially more negative anomalies and fewer positive responses during MYDs in the DM simulation. Temperate PFTs show  
445 a similar but weaker shift, while boreal PFTs show only minor changes, with nearly identical distributions of GPP anomalies during MYDs. Overall, adding drought-induced mortality increases the sensitivity of tree productivity to MYDs, particularly in tropical regions.



**a) Baseline model**



**b) DM model**

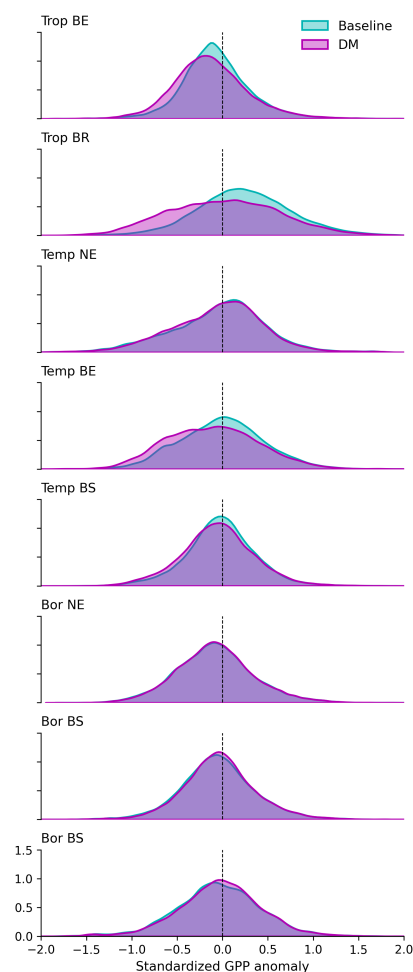
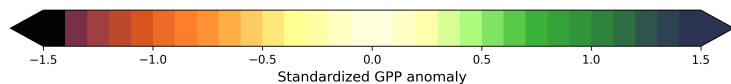
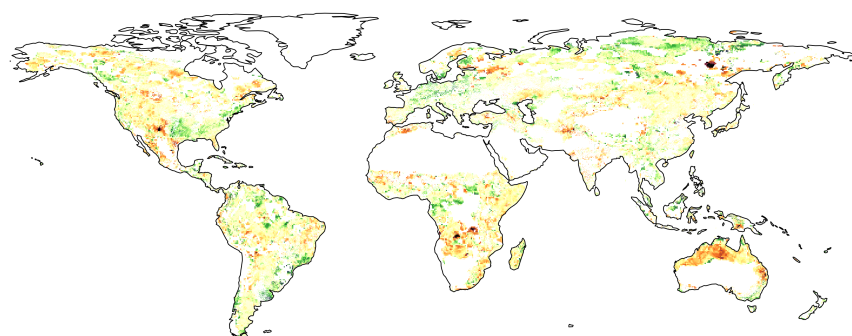


**Figure 11.** Tree  $GPP_{SA}$  during multi-year droughts (MYDs) for the baseline and drought mortality (DM) simulations. Maps show the mean  $GPP_{SA}$  anomaly during MYDs, while the distributions show responses for individual PFTs. More negative values indicate stronger reductions in GPP during drought conditions. PFT abbreviations are: Trop BE (tropical broadleaved evergreen), Trop BR (tropical broadleaved raingreen), Temp NE (temperate needleleaved evergreen), Temp BE (temperate broadleaved evergreen), Temp BS (temperate broadleaved summergreen), Bor NE (boreal needleleaved evergreen), Bor BS (boreal broadleaved summergreen), and Bor NS (boreal needleleaved summergreen).



## 4 Discussion

The representation of drought-induced tree mortality remains a major challenge in dynamic global vegetation models. In this study, we introduced a drought mortality formulation in LPJmL-5 to increase the sensitivity of tree mortality to water stress. The results show that this formulation substantially changes drought-related mortality responses, particularly for tropical and temperate tree PFTs, while having limited effects on simulated GPP and LE under normal conditions.

### 4.1 Drought mortality formulation

Tree mortality during droughts is difficult to represent in DGVMs because it arises from a complex interaction of hydraulic failure, carbon starvation, biotic agents, and pre-existing stress conditions (Hajek et al., 2020; Fischer et al., 2025). Consequently, most DGVMs rely on growth-efficiency or age-based mortality formulations (Manusch et al., 2012; Bugmann et al., 2019). LPJmL-5 follows this simplification and represents mortality using a growth-efficiency-based formulation, meaning that drought affects mortality only indirectly through reduced productivity. In addition, mortality is constrained by a maximum annual rate of 3% yr<sup>-1</sup>. As a result, productivity can decline under drought, but the extent to which water stress can cause increased mortality rates is limited. Therefore, post-drought recovery can be relatively fast in the model, since biomass losses due to mortality are limited. Similar limitations, particularly the underestimation of drought-induced mortality, have also been reported for other DGVMs (Fischer et al., 2025).

The drought mortality formulation introduced in this study (Equation 8) is designed to link mortality to water stress. While it is inspired by the concept of hydraulic failure, it does not simulate the underlying hydraulic processes. Hydraulic failure is typically linked to xylem tensions and losses in hydraulic conductivity, with mortality often occurring once conductivity losses become severe (Hammond et al., 2019). Because LPJmL-5 does not simulate xylem water potentials or hydraulic conductance, a direct representation of these processes is not possible. Instead, the formulation relies on variables that are already available in LPJmL-5. The water stress scalar (*wscal*) reflects the balance between actual transpiration and atmospheric demand and therefore provides a useful indicator of plant water stress. Phenology is included to ensure that mortality mainly occurs when leaves are present, while VPD represents the additional atmospheric demand that can amplify drought stress by increasing transpiration losses.

Our results show that in the baseline LPJmL-5 simulation, mortality responds only weakly to drought, whereas adding an explicit drought mortality formulation leads to a substantially stronger response (Figure 6). This behaviour is consistent with Fischer et al. (2025), who found that most DGVMs underestimate drought-induced tree mortality. Beyond mortality, similar patterns are also evident in vegetation productivity. The baseline model shows only limited changes in GPP during drought events, whereas the DM simulation produces stronger GPP reductions, particularly in tropical PFTs (Figures 10 and 11). While mean GPP<sub>SA</sub> during MYDs changes little overall, tropical tree PFTs consistently show more negative anomalies when drought mortality is included. At the regional scale, the DM simulation also shows slower post-drought recovery, particularly in Australia, addressing a known limitation of LPJmL-5, which tends to recover too quickly after severe drought events (Ruijsch et al., 2026).



Drought-induced mortality has also been implemented in other DGVMs. For example, LPJ-GUESS-HYD includes hydraulic processes and links tree mortality to hydraulic failure (Meyer et al., 2025). Similarly, ORCHIDEE-CAN-NHA represents water transport within trees and links drought mortality to hydraulic stress (Yao et al., 2022). These approaches provide a more detailed representation of how drought can lead to tree mortality. In contrast, our formulation uses a simpler approach based on variables already available in LPJmL-5, allowing drought mortality to be represented globally across PFTs without adding a separate hydraulic model. This comes at the cost of less process detail, but makes the formulation easier to apply at the global scale.

Overall, introducing a drought mortality formulation increases the sensitivity of LPJmL-5 to drought, particularly in tropical forests, while largely preserving the model's ability to reproduce observed GPP and LE. Validation against FLUXNET observations shows that GPP and LE remain very similar between the baseline and DM simulations (Figure 7), indicating that the new formulation mainly affects vegetation dynamics under drought stress rather than altering overall model behaviour. The limited changes in total GPP and LE may partly be attributed to compensation by other, more drought resilient, vegetation types. As some trees die, the remaining vegetation can make use of additional light, water, and nutrients, which helps offset productivity losses (Wang et al., 2012a). Therefore, higher mortality rates do not necessarily translate into structural changes in total GPP and LE. Although direct validation of mortality remains difficult, the combined response of mortality and GPP suggests that the DM formulation captures key aspects of vegetation dynamics under drought that are missing in the baseline LPJmL-5 configuration.

## 4.2 Limitations and interpretation of the calibration of $\alpha$ and $\beta$

A major limitation of this study is the limited availability of observational mortality data. The calibration therefore mainly relies on the mortality–drought relationship reported by Greenwood et al. (2017), as consistent global time series of tree mortality are not yet available. While this relationship provides a useful benchmark, it only captures site-level relationships between drought conditions and observed mortality rates. In addition, this theoretical relationship also has limitations when it comes to capturing time-delayed drought response due to reduced vegetation health leading to delayed die-off of vegetation. There are also uncertainties in the GPP calibration target. MODIS GPP products contain mixed vegetation signals, even after filtering for dominant land-cover types. In addition, productivity responses to drought can be influenced by lagged effects and other environmental drivers unrelated to drought. As a result, the observational targets used here should be seen as approximations rather than strict benchmarks.

Despite these uncertainties, the calibration shows clear differences in drought sensitivity between plant functional types (Table 1, Figure 5). Broadleaved summergreen and raingreen trees show the strongest mortality responses, while evergreen and needleleaved PFTs are more resistant. This matches known trait differences, as needleleaved trees are generally more drought resistant than broadleaved trees (Winter Artusio et al., 2025; Carnicer et al., 2013). The exact parameter values should still be interpreted with care, since the calibration was based on a limited number of sites rather than a global optimisation. They should therefore be seen as indicative model parameters rather than direct estimates of how sensitive plants are to drought stress.



### 515 4.3 Other limitations and uncertainties

A limitation of this study is the conversion of background and heat stress mortality from an annual to a monthly timescale. Because these mortality processes are only calculated annually in the baseline LPJmL-5, implementing them directly on a monthly basis would require substantial changes to the model code. Instead, annual mortality rates were distributed over the following year. While this approach is not fully realistic, it allows drought mortality to be applied on a monthly timescale  
 520 without introducing major changes to the model. Sensitivity tests (Section S1) showed that this modification has only minor effects on simulated FPC and GPP. Nevertheless, a fully monthly representation of all mortality processes would likely be more realistic.

Another limitation is that LPJmL-5 does not explicitly simulate individual trees. Instead, each tree PFT within a grid cell is represented by a single average tree that is scaled by the population density. As a result, the model does not represent  
 525 variation in tree age or size within a PFT, and all trees of that PFT respond identically to drought. Likewise, vegetation recovery is represented by changes in population density rather than by the growth of new individual trees. This simplification may influence simulated mortality and post-drought recovery, particularly after severe drought events.

Additional uncertainty arises from the observational data used for model evaluation. FLUXNET sites vary considerably in record length, with only a few sites providing long-term observations spanning more than 15 years, while many cover only 3–5  
 530 years. This uneven coverage makes it harder to assess long-term variability and trends, and also limits how representative the validation is at the global scale. In addition, FLUXNET observations come with their own uncertainties related to gap-filling, flux partitioning, and energy balance closure, which should be considered when evaluating model performance (Pastorello et al., 2020).

Further uncertainty arises from the choice of meteorological forcing data and its temporal resolution. Ruijsch et al.  
 535 (2026) showed that both factors can substantially influence simulated GPP in LPJmL-5. In this study, the bias-corrected W5E5 dataset was used at daily temporal resolution (Lange et al., 2022), as it provides high-frequency climate forcing and yields GPP estimates closest to observations (Ruijsch et al., 2026).

Finally, there is also uncertainty associated with the drought definition used in this study. Drought events were identified using SPEI, which combines precipitation and potential evapotranspiration and therefore captures both water availability and  
 540 atmospheric demand (Vicente-Serrano et al., 2010). SPEI-12 was selected because it is widely used in studies of MYDs (Venkataraman et al., 2016; Tarafdar and Dutta, 2023; Ruijsch et al., 2025; van Mourik et al., 2025; Češljár et al., 2024; Odongo et al., 2025) and because it is the same drought metric used by Greenwood et al. (2017) to describe the relationship between drought and tree mortality. However, using a different drought metric or accumulation period could lead to different functional relationships between the drought indicator and the vegetation drought responses.

### 545 4.4 Outlook for drought mortality modelling

Although the effects on present-day global GPP and LE were limited, the rain exclusion experiment suggests that the new drought mortality formulation becomes increasingly important under severe drought conditions (Figure 9). The shorter e-



folding timescales indicate that vegetation responds more quickly to prolonged drought stress, suggesting that differences between the baseline and DM models may become much larger under future climate conditions.

550 Future work could therefore focus on using the drought mortality formulation in climate change scenarios, where drought frequency, duration, and intensity are expected to increase. In addition, future model development could include hydraulic failure and carbon starvation, as implemented in models such as LPJ-GUESS-HYD and ORCHIDEE-CAN-NHA (Meyer et al., 2025; Yao et al., 2022).

555 Overall, this study demonstrates that a relatively simple drought mortality formulation can substantially improve drought-related mortality responses in LPJmL-5 while maintaining realistic carbon and water fluxes. These results suggest that including drought mortality is an important step towards more realistic simulations of forest responses to drought stress.



## 5 Conclusion

In this study, we improved the representation of drought-induced tree mortality in LPJmL-5 by implementing a new drought mortality scheme based on water stress, VPD, and phenology. The scheme uses two PFT-specific parameters,  $\alpha$  and  $\beta$ , where  $\alpha$  determines when drought-induced mortality starts and  $\beta$  determines how quickly mortality increases once this threshold is reached. These parameters were calibrated using a multi-objective optimisation approach that considered both observed mortality and GPP responses during drought events.

The calibrated parameter values produce mortality responses that are generally consistent with known differences between PFTs and improve the agreement between simulated and observed drought–mortality relationships. Compared to the baseline model, the DM model results in a more realistic response of mortality to drought, especially for tropical and temperate tree PFTs.

Although the new mortality scheme has only a limited impact on global mean GPP and LE, it does affect vegetation dynamics during drought conditions. In several regions, drought impacts become more severe and the rapid post-drought recovery spikes in GPP seen in the baseline simulation are reduced. This suggests that the DM model represents the effects of drought on vegetation in a more realistic way.

Overall, the results show that a relatively simple drought mortality formulation can improve the representation of drought responses in LPJmL-5 without negatively affecting large-scale carbon and water fluxes. Including drought-induced mortality is therefore an important step towards more realistic simulations of forest responses to drought stress.



## Appendix A Datasets used in this study

575 In this study, LPJmL-5 was forced with meteorological, soil, and land-use inputs derived from observational datasets (Table A1). Daily meteorological forcing was obtained from the W5E5 dataset and includes temperature, precipitation, downward longwave and shortwave radiation, and wind speed (Lange et al., 2022). Annual atmospheric CO<sub>2</sub> concentrations were taken from Büchner and Reyer (2022). Soil inputs include soil pH (Volkholz and Müller, 2020), soil type (Knoben, 2021), and nitrogen deposition (Yang and Tian, 2023). Land use was taken from the dataset developed by Ruijsch et al. (2026), which

580 is based on the IFPRI crop area maps (International Food Policy Research Institute (IFPRI), 2024). All input datasets were regridded to a 0.1° spatial resolution. The calibration objective functions were based on SPEI-12 (Ruijsch et al., 2026) and MODIS GPP (Didan, 2015a, b).

**Table A1.** Overview of datasets and variables used in this study.

| Dataset / Variable                                         | Temporal range | Temporal resolution | Spatial resolution | Reference                  |
|------------------------------------------------------------|----------------|---------------------|--------------------|----------------------------|
| <b>LPJmL-5 Input</b>                                       |                |                     |                    |                            |
| Precipitation [mm/day]                                     | 1901–2019      | Daily               | 0.5°               | Lange et al. (2022)        |
| Temperature [°C]                                           | 1901–2019      | Daily               | 0.5°               | Lange et al. (2022)        |
| Wind speed [ $\text{m s}^{-1}$ ]                           | 1901–2019      | Daily               | 0.5°               | Lange et al. (2022)        |
| Downward longwave radiation [ $\text{W m}^{-2}$ ]          | 1901–2019      | Daily               | 0.5°               | Lange et al. (2022)        |
| Downward shortwave radiation [ $\text{W m}^{-2}$ ]         | 1901–2019      | Daily               | 0.5°               | Lange et al. (2022)        |
| CO <sub>2</sub> concentration [ppm]                        | 1901–2019      | Annual              | Global             | Büchner and Reyer (2022)   |
| NH <sub>x</sub> deposition [ $\text{g/m}^2/\text{month}$ ] | 1901–2019      | Monthly             | 0.5°               | Yang and Tian (2023)       |
| NO <sub>y</sub> deposition [ $\text{g/m}^2/\text{month}$ ] | 1901–2019      | Monthly             | 0.5°               | Yang and Tian (2023)       |
| Soil pH                                                    | -              | -                   | 0.5°               | Volkholz and Müller (2020) |
| Soil type                                                  | -              | -                   | 250 m (0.25 km)    | Knoben (2021)              |
| Land use                                                   | 2020           | -                   | 0.1°               | Ruijsch et al. (2026)      |
| <b>Drought Index</b>                                       |                |                     |                    |                            |
| SPEI-12                                                    | 1901–2019      | Monthly             | 0.5°               | Ruijsch et al. (2026)      |
| <b>Remote Sensing Dataset</b>                              |                |                     |                    |                            |
| MODIS GPP                                                  | 2000–2019      | 16-day              | 1 km               | Didan (2015a, b)           |
| <b>Site-level Dataset</b>                                  |                |                     |                    |                            |
| FLUXNET2015 GPP and LE                                     | Site-dependent | Monthly             | Flux tower site    | Pastorello et al. (2020)   |



**Appendix B Calibration objective functions and locations**

The objective slopes and intercepts used for the calibration objective functions are listed in Table B1. Mortality objectives are based on Greenwood et al. (2017), while GPP objectives were derived from the MODIS GPP product Didan (2015a, b). Figure B1 shows the calibration locations used in the multi-objective optimisation of  $\alpha$  and  $\beta$ .

**Table B1.** Objective GPP and mortality slopes and intercepts by plant functional type.

| Plant functional type                   | GPP slope | GPP intercept | mortality slope | mortality intercept |
|-----------------------------------------|-----------|---------------|-----------------|---------------------|
| Tropical broadleaved evergreen trees    | 0.14      | 0.02          | -0.46           | -1.96               |
| Tropical broadleaved raingreen trees    | 0.03      | 0.03          | -0.46           | -1.96               |
| Temperate needleleaved evergreen trees  | 0.12      | 0.02          | -0.46           | -1.96               |
| Temperate broadleaved evergreen trees   | 0.17      | 0.04          | -0.46           | -1.96               |
| Temperate broadleaved summergreen trees | 0.18      | 0.04          | -0.46           | -1.96               |
| Boreal needleleaved evergreen trees     | 0.08      | 0.01          | -0.46           | -1.96               |
| Boreal broadleaved summergreen trees    | 0.08      | 0.00          | -0.46           | -1.96               |
| Boreal needleleaved summergreen trees   | 0.10      | 0.01          | -0.46           | -1.96               |

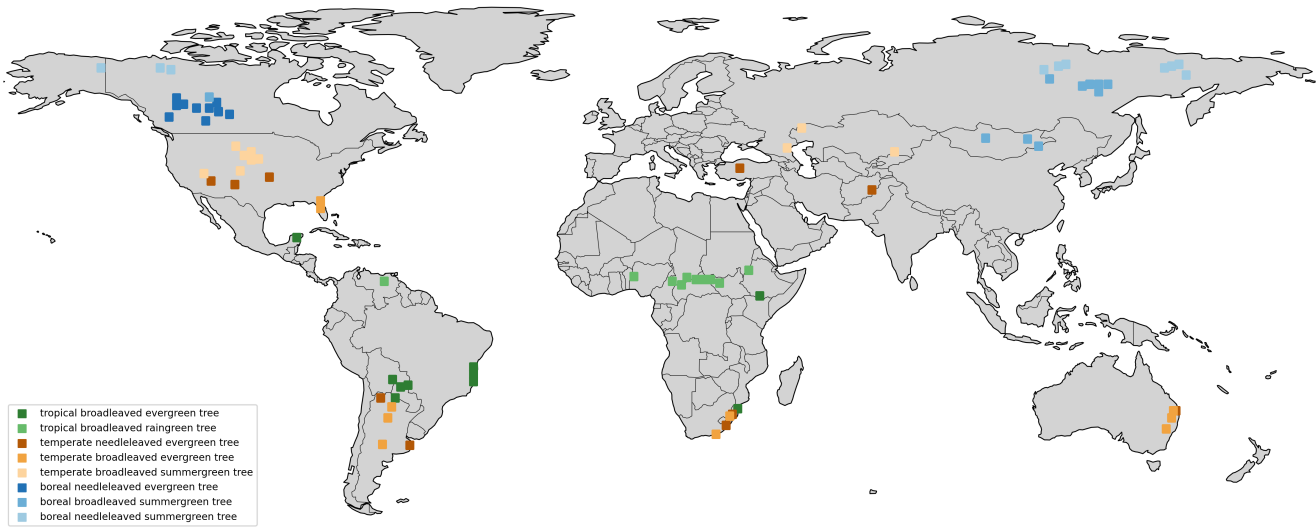


**Figure B1.** 8 × 8 grid-cell blocks used in the multi-objective optimisation of  $\alpha$  and  $\beta$ . For each tree PFT, blocks were selected in water-limited regions based on highest fractional plant cover (FPC) and required a minimum distance of 200 km.



## Appendix C Percentage tree cover and chosen focus regions

Figure C1 shows the percentage of tree cover in 2019 from the DM simulation at  $0.1^\circ$  degree spatial resolution. The selected focus regions are California (CAL), the Rhine–Meuse delta in Western Europe (WEU), the Brahmaputra River basin (BRA), central Argentina (ARG), the Orange River basin in southern Africa (SA), and the Murray–Darling basin in Australia (AUS). These regions correspond to those used by (Ruijsch et al., 2025) and were chosen based on the occurrence of MYDs, geographic and climatic diversity, and variation in vegetation types.

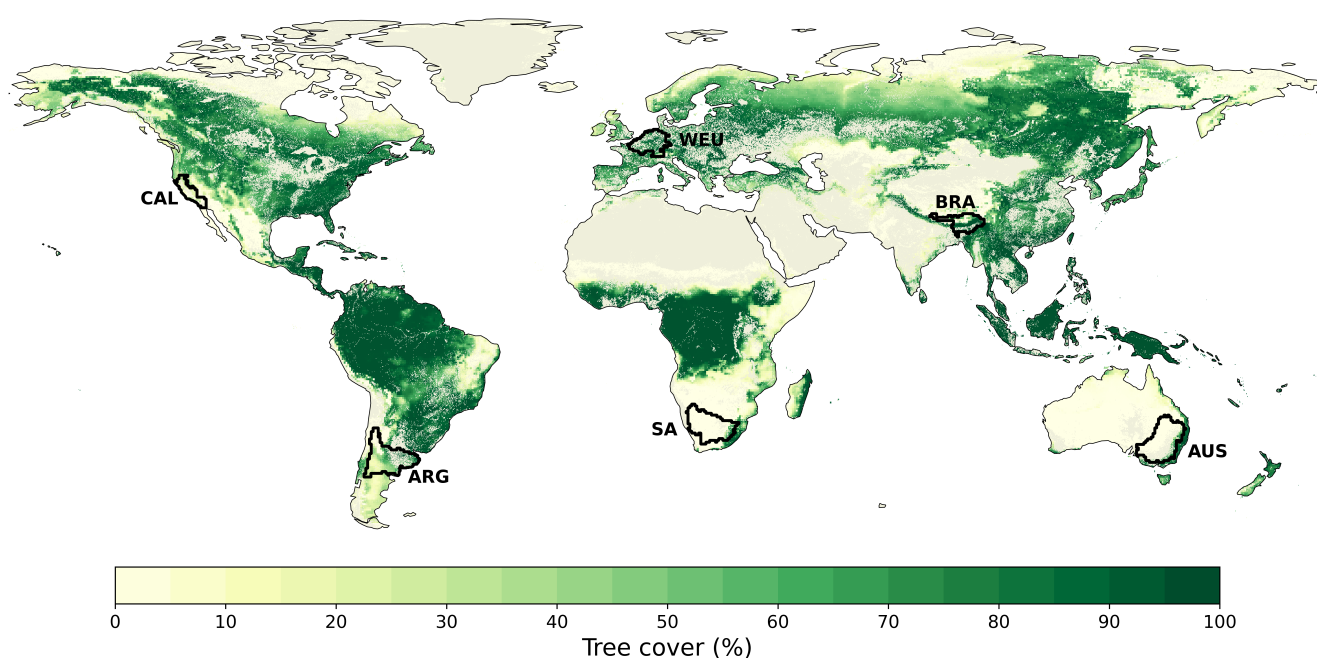


**Figure C1.** Percentage tree cover in the DM simulation (2019). Selected focus regions are outlined in black.



*Code and data availability.* The simulations were performed using LPJmL-5, with modifications to the drought-induced mortality scheme described in this study. The LPJmL-5 source code is openly available at <https://github.com/PIK-LPJmL/LPJmL>. This study uses version 5.10.1 (released on May 20 2026). The modified source code and scripts required to reproduce the simulations and analyses are available at <https://doi.org/10.5281/zenodo.22811633> (Ruijsch, 2026). All processed data and model outputs required to reproduce the analyses are available at: <https://doi.org/10.24416/UU01-B4VK1T> (Ruijsch and Wanders, 2026). The raw datasets are publicly available from their respective sources (see Table A1).

*Author contributions.* **DR:** Conceptualisation, methodology, software, validation, formal analysis, data curation, writing–original draft, visualisation. **SH:** Conceptualisation, formal analysis, writing–review and editing. **MB:** Conceptualisation, methodology, writing–review and editing. **WB:** Software, writing–review and editing. **HB:** Conceptualisation, formal analysis, writing–review and editing. **NW:** Conceptualisation, formal analysis, writing–review and editing, project administration, funding acquisition.

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