Grassland vulnerability to climate change varies by region and season through productivity-stability trade-offs

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Abstract

Understanding the vulnerability of permanent grasslands to climate change is essential for sustaining forage production and other ecosystem services. Potential adaptation levers include adjustments in management strategies and the selection of plant functional types (PFTs). This study quantifies changes in biomass yield and interannual stability of temperate permanent grasslands under future climate scenarios, using Gras-Sim, a process-based model integrating climate, soil management, and PFT composition. Simulations were performed for contrasting agricultural regions at +2 °C, +3 °C, and +4 °C warming levels, using downscaled CMIP6 projections (CMCC, MIR, MPI) with corresponding CO_2 trajectories. Significant interactions between region, climate model, and PFT ($P < 0.001$) revealed context-dependent responses. In high-altitude regions such as the High Ardennes, annual yields increased by up to 2.52 t DM ha^{-1} compared to the historical baseline (1981-2010). Across all scenarios, PFT B (e.g. *Dactylis glomerata*) exhibited significantly higher yields, while PFT A (e.g. *Lolium perenne*) showed significantly higher interannual stability, confirming a productivity-stability trade-off. Seasonal shifts were more pronounced under MIR +4 °C, with spring yields increasing by 4.5 t DM ha^{-1} and summer yields decreasing by 2.4 t DM ha^{-1} relative to historical baselines ($P < 0.001$). The frequency of pixel-years without a summer cut increased up to 14% under MIR at +4 °C, highlighting an emergent signal of production collapse during peak drought. These results support the need for adaptation strategies that combine functional complementarity, flexible management, and spatially explicit simulation tools to sustain grassland productivity and stability under climate change.

Key words: process-based modeling, plant functional types, forage yield, interannual variability, climate scenarios, cutting management.

1. Introduction

Permanent grasslands are crucial to temperate ecosystems, providing forage for herbivores and contributing to climate regulation and biodiversity preservation (Soussana and Duru, 2007; Bengtsson et al., 2019; Bardgett et al., 2021). They are also important for ecosystem multifunctionality, supporting services such as pollination, habitat provision, nutrient cycling, and erosion control (Gaujour et al., 2012; Liu et al., 2023; Allart et al., 2024), in addition to cultural services and aesthetic value. In Europe, permanent grasslands account for 34% of the utilized agricultural area (UAA) (Schils et al., 2022). Because of their central role in ecosystem functioning, grassland vulnerability to climate change has broad ecological and agricultural implications.

In addition to changes in overall productivity, climate change is also expected to reshape the seasonal distribution of grassland growth. An earlier onset of vegetation development is a widely observed response of herbaceous plants to warming, especially in temperate grasslands (Piao et al., 2019; Huang et al., 2020). Long-term records of cool-season grasses such as *Lolium perenne* already show a trend toward earlier reproductive development (Gilliland et al., 2025). While these shifts may increase spring productivity, they can also decrease resilience to summer droughts, resulting in imbalances in seasonal growth and increased interannual variability of forage supply.

Vulnerability is a multifaceted concept that is often used to analyze sensitivity, exposure, and the ability to adapt to natural environments (Pacifici et al., 2015). More precisely, it can be defined as the sensitivity and resilience of ecosystems to external disturbances, such as climate change and human activities, at a given scale of time and space (Li et al., 2018). In grassland systems, vulnerability depends on weather conditions as well as soil properties, species richness, management practices, and the interactions among these factors. Species-rich grasslands tend to be more resistant to climate extremes, maintaining more stable productivity under such conditions (Isbell et al., 2015). In European calcareous grasslands, regular mowing increases diversity in mesic systems, while drought reduces diversity in xeric systems, demonstrating that responses depend on local pedoclimatic context and management (Maalouf et al., 2012). However, the complexity of grassland ecosystems and the uncertainty of future climate conditions make it difficult to explore adaptation strategies through field experiments alone. Although field experiments are essential, they are limited in time, space, and the range of scenarios they can address. This motivates quantitative approaches designed to identify the mechanisms through which pedoclimatic heterogeneity and functional composition mediate grassland responses to climate change. Simulation-based analyses can therefore serve as exploratory platforms, allowing climate, soil and management drives to be integrated without losing sight of ecological mechanisms.

Functional traits, defined as morphological, biochemical, physiological, structural, phenological, or behavioral characteristics expressed in phenotypes, are key to understanding how species respond to environmental drivers and influence ecosystem functioning (Díaz et al., 2013). In grasslands, such traits mediate plant responses to soil nutrient availability and management practices (e.g., grazing intensity, cutting frequency, fertilization), while also underpinning contributions to ecosystem services such as forage production, landscape openness, and biodiversity maintenance. To operationalize this functional diversity, plant functional types (PFTs) have been proposed as groups of species sharing contrasting trait profiles. This replaces long species lists with a smaller set of functional strategies suited for agronomic diagnostics and modeling (Cruz et al., 2002, 2010). In temperate grasslands, the initial topology classified 17 grass species into four functional groups (Cruz et al., 2002): Type A includes early developing species with rapid growth but low standing biomass accumulation (e.g. *Lolium perenne*); Type B comprises later-developing species with greater biomass accumulation (e.g. *Dactylis glomerata*); Types C and D correspond to slow-growing, lower-quality species with late phenology (e.g. *Festuca rubra*, *Briza media*). This classification was later expanded to six PFTs to accommodate a broader range of temperate grass species, increasing the coverage from 17 to 38 species (Cruz et al., 2010). In grassland process-based models, PFTs enable contrasting responses to environmental conditions and management to be represented without tracking each species individually, which is particularly useful in species-rich permanent grasslands. Empirical studies confirm that functional groups exhibit different sensitivities to climatic stresses. For instance, *Dactylis glomerata* (PFT B) sustains comparatively higher production under water deficit by mobilizing carbohydrate reserves, whereas *Lolium perenne* (PFT A) shows sharper declines in biomass and poorer persistence (Turner et al., 2012). At the physiological level, resilience to extreme events has been shown to depend on carbohydrate metabolism in meristems with *Dactylis glomerata* exhibiting markedly higher tolerance than other species (Volaire et al., 2020). In temperate Europe, productive permanent grasslands often include high-yielding forage grasses, such as perennial ryegrass (*Lolium perenne*, PFT A) and cocksfoot (*Dactylis glomerata*, PFT B). These species are frequently mentioned in the literature as important components of managed temperate grasslands (Żurek et al., 2012; Muylle et al., 2015). Given their agronomic relevance and widespread use, PFTs A and B capture functional strategies that are particularly representative of managed permanent grasslands in Wallonia.

Instead of focusing on improving a single drought-tolerant species, such as cocksfoot, a more informative approach is to contrast the functional strategies that co-occur in temperate grasslands. Examining both PFT A and PFT B reveals the key trade-offs among productivity, phenology, and stress responses, which would not be evident when studying *Dactylis glomerata* in isolation. Although legumes and forbs are present in permanent grasslands, the current version of the model does not explicitly represent their dynamics, as it was primarily calibrated and validated for cool-season perennial C3 grasses (Kokah et al., 2023). Consequently, our analysis focuses on the two dominant grass functional types (PFT A and PFT B), for which the model provides validated physiological and production responses.

Belgium offers a representative case for temperate Europe, where permanent grasslands display strong contrasts in soil depth, texture and altitude. About 66% of the national permanent grasslands are in Wallonia (SPW Agriculture, 2024a), the southern part of the country, which lies in a temperate oceanic climate. In 2023, they represented 41.8% of the UAA in Wallonia (SPW Agriculture, 2024a). These systems are already experiencing the effects of climate change, including repeated summer droughts, uneven rainfall distribution, damaging frosts, and early heat waves at the end of winter (IRM, 2025). These factors disrupt the regularity of grass growth and make pasture-based systems more vulnerable by exposing farmers to fodder shortages (Decruyenaere, 2022). Walloon permanent grasslands are considered representative of temperate Western European systems as they share key biophysical features across the Atlantic-continental gradient. These features include similar soil type ranges, comparable mesophilous grass species pools, and a livestock-based management system that combines grazing and cutting. These characteristics mirror the structural and functional attributes of temperate European grassland systems, making Belgium an appropriate case study for exploring agroecological responses to climate change.

This study aims to assess the vulnerability of temperate permanent grasslands to future climate conditions by quantifying the spatial and seasonal patterns of productivity and interannual stability resulting from the interactions between climate forcing, soil diversity, and plant functional strategies. We analyze two contrasting grassland types, each dominated by a different plant functional type (*Lolium perenne* for PFT A and *Dactylis glomerata* for PFT B), under uniform management and across a range of projected climate scenarios. Belgium serves as a representative case study for temperate Europe, characterized by strong pedoclimatic gradients that allow for the explicit exploration of regional contrasts in grassland vulnerability. By linking simulated spatial patterns to the underlying ecophysiological mechanisms in Gras-Sim, this study aims to improve the understanding of how productivity-stability trade-offs influence grassland vulnerability to climate change. Accordingly, the following hypotheses were formulated:

(1) Vulnerability is not solely a function of mean climate warming but emerges from interactions between local climate variations and soil conditions.
(2) PFT B (e.g. *Dactylis glomerata*) is expected to be more productive under climate stress, whereas PFT A (e.g. *Lolium perenne*) may show more stable interannual growth due to its more regular phenology.
(3) Growth dynamics are expected to shift, reflecting phenological responses to warming with reduced summer production and increased growth in spring and fall.

2. Material and methods

2.1. Plant functional types and parameterization

We used the functional typology established by Cruz et al. (2002, 2010), which groups temperate grass species into plant functional types (PFTs) based on shared phenological and morphological characteristics. In this study, only one species was selected to represent each PFT. Perennial ryegrass (*Lolium perenne*) represented PFT A and cocksfoot (*Dactylis glomerata*) represented PFT B as these species are among the most common representatives of the dominant functional strategies observed in productive permanent grasslands in Western Europe and Wallonia. PFT A comprises early, fast-growing species that are characterized by a short leaf lifespan, a high specific leaf area, and high digestibility during the vegetative stage. These traits support rapid biomass production under frequent defoliation. PFT B corresponds to relatively later-developing, more conservative species with longer-lived leaves, lower specific leaf area, and a greater capacity to accumulate standing biomass. These differences provide the necessary functional contrast to investigate productivity-stability trade-offs.

Each PFT is parameterized using a set of phenological, structural, and physiological attributes in the model. Phenology is defined by the thermal time requirements for the onset (ST1) and completion (ST2) of the reproductive period. Structural traits include specific leaf area (SLA) and leaf lifespan (LLS). Seasonal modulation of growth is represented by minimum and maximum seasonal effects (minSEA and maxSEA, respectively). Digestibility dynamics are described by the maximum and minimum organic matter digestibilities of green vegetative and reproductive tissues (maxOMDGV, minOMDGV, maxOMDGR, and minOMDGR). Biomass structure is represented by bulk density parameters (BDGV, BDGR, BDDV, and BDDR). The temperature responses of growth are defined using the base temperature (T0), plateau temperature (T1), decline temperature (T2), and the upper temperature limit (Tlimit), combined with the minimum cumulative temperature requirement for growth (STmin). The full set of parameters and corresponding values for PFT A and PFT B is provided in Table S1.

2.2. Weather and soil data

2.2.1. Historical and future climate data

The historical weather data (air temperature, solar radiation, daily precipitation, and reference evapotranspiration) were extracted from the ERA5 reanalysis dataset, developed by the European Center for Medium-Range Weather Forecasts (ECMWF). These data were dynamically downscaled using MAR v3.14 (Regional Atmospheric Model), a physically based regional climate model well suited for high-resolution climate impact simulations. The MAR simulations were performed at 5 km × 5 km spatial resolution, consistent with studies on climate impacts in European agriculture (Fettweis et al., 2024). A 30-year reference period (1981-2010) was selected to represent the historical climate baseline, in accordance with IPCC (Intergovernmental Panel on Climate Change) guidelines for climate impact assessments.

Future climate projections were downscaled with the same MAR configuration to ensure consistency with the historical baseline. Future weather data were based on warming levels of +2 °C, +3 °C and +4 °C above pre-industrial levels, consistent with the Shared Socioeconomic Pathways (SSPs) defined in the Coupled Model Intercomparison Project (CMIP6; Eyring et al., 2016). To capture a range of possible climate futures, three CMIP6 global climate models (GCMs) with contrasted temperature and precipitation responses over Europe were selected following the recommendations from the EURO-CORDEX community (Sobolowski et al., 2025):

- CMCC-CM2-SR5, dry and moderately warm scenario (CMCC);
- MPI-ESM1-2-HR, intermediate scenario (MPI);
- MIROC6, warm and wetter tendency, scenario with known warm/moist bias (MIR).

The simulation period runs from 2024 to 2100, with time windows of 30 years for the +2 °C and +3 °C scenarios and 20 years for the +4 °C scenarios (Table 1). This shorter window reflects the later occurrence and reduced duration of periods reaching +4 °C warming in CMIP6 models. Moreover, the selected years differ between GCMs, since each model reaches the warming levels at a different pace. This approach follows IPCC recommendations to analyze climate impacts at specific global warming levels rather than fixed time periods. The associated CO_2 concentration (Table 1) was estimated as the mean value within each time window and assumed constant over the period, based on concentration-driven CMIP6 datasets provided by input4MIPs (Meinshausen et al., 2017). Supplementary figures summarize historical and future temperature and precipitation patterns at the regional scale (Figures S1-S4).

2.2.2. Soil properties and spatial layers

The soil input data used for simulations includes soil texture, and organic matter content, which are crucial for simulating water availability. The primary source for soil texture data was the ISRIC SoilGrids250m dataset (Hengl et al., 2017), developed by the International Soil Reference and Information Center. This dataset provides global soil properties at multiple depth intervals and a spatial resolution of 250 m x 250 m. To refine global layers with region-specific information where available, data on total organic carbon (TOC) were supplemented using regional soil information (Chartin et al., 2017). All data layers were projected to a common coordinate reference system and resampled to match the 250 m grid in the model. In Gras-Sim, soil water holding capacity is derived from soil texture and organic matter content using an empirical formulation that determines plant-available water (Kokah et al., 2023). This formulation combines the relative proportions of sand and clay with soil organic matter content to represent spatial variability in soil water availability across the landscape. Soil depth is not explicitly considered a limiting factor in the simulations since Gras-Sim represents soil water dynamics within the top 1 m of the soil profile. Consequently, spatial contrasts in simulated water availability primarily reflect differences in soil texture and organic matter content rather than total soil depth. The spatial distribution of the main soil types of Wallonia is shown in Figure S5.

2.2.3. Growing season definition

To ensure consistency across simulations and climate scenarios, all analyses were based on a common definition of the growing season, which used fixed day-of-year (DOY) intervals. The growing season was defined as DOY 60 to 334, which corresponds to approximately March 1 to November 30. Within this period, three seasons were identified:

- Spring: DOY 60 to 181 (approximately March 1 to June 30)
- Summer: DOY 182 to 243 (approximately July 1 to August 31)
- Autumn: DOY 244 to 334 (approximately September 1 to November 30)

This calendar-based definition reflects the typical phenology of temperate grasslands and ensures comparability across regions, climate models, and warming levels. In managed temperate grasslands, seasonal analyses often use calendar-based partitions of the grazing or growing season. These partitions typically distinguish between spring (March-May), summer (June-August), and autumn (September-November), which correspond to different phases of grass growth and management activity (Chang et al., 2017). Extending the spring period to include June enables spring cuts to account for the biomass accumulated during the late spring growth phase. The winter period (DOY 1 to 59 and 335 to 365) was excluded because biomass production is negligible and no cuts occur during this time.

2.2.4. ETCCDI climate indices

To better characterize extreme climatic conditions that could affect grassland productivity in the future, three indices from the ETCCDI (Expert Team on Climate Change Detection and Indices) reference system were calculated annually for each climate scenario, based on daily data series. All indices were computed only over the growing season (DOY 60-334) to ensure they reflected conditions relevant to grass growth and management. The indices used are as follows:

- TXx: seasonal maximum temperature (°C), defined as the maximum daily temperature over the growing period;
- RX5day: maximum precipitation over five consecutive days (mm) within the growing period; an indicator of extreme rainfall events;
- CDD: consecutive dry days, defined as the maximum seasonal duration of drought, calculated as the longest sequence of consecutive days with daily precipitation strictly less than 1 mm within the growing period.

These indices were extracted annually for the nine climate model-warming combinations and compared with historical data.

2.3. Pedoclimatic drivers of grassland productivity in Wallonia

Wallonia comprises ten agricultural regions that differ in soil, climate, and topography (Figure 1). Strong spatial gradients in drainage conditions, soil texture and water-holding capacity are characteristic of these regions, as illustrated by the detailed soil map in Figure S5. Climatic conditions also vary significantly from region to region, with differences in precipitation amounts, temperature regimes, and length of the growing season following the main topographic gradients. Together, these pedoclimatic gradients are therefore expected to have a strong influence on grassland productivity and stability across Wallonia. Substantial within-region heterogeneity in soil properties further justifies the use of spatially explicit simulations before regional aggregation. This pedoclimatic heterogeneity, summarized in Table 2 (SPW Agriculture, 2024b; Forton and Meniger, 2020) and illustrated in Figure S5, motivates the modeling strategy adopted in this study, wherein simulations are performed at the pixel (cluster) scale.

2.4. Gras-Sim model

Gras-Sim (Kokah et al., 2023) is a process-based model designed to simulate the growth of permanent grasslands by integrating weather data, soil properties, management practices, and the ecophysiological characteristics of dominant species grouped into plant functional types (PFTs). In this study, the model is used as an operational framework to investigate how ecological mechanisms (functional composition, soil heterogeneity, climate drivers) condition grassland productivity and stability under contrasting climate scenarios.

2.4.1. Model description and CO_2 effect function

Gras-Sim simulates the daily dynamics of permanent grasslands. Biomass is represented in four compartments: green vegetative biomass (BMGV, kg DM ha^{-1}), dead vegetative biomass (BMDV, kg DM ha^{-1}), green reproductive biomass (BMGR, kg DM ha^{-1}), and dead reproductive biomass (BMDR, kg DM ha^{-1}). The model integrates water and nitrogen dynamics, with transfer processes between soil and plant. Two different PFTs, A and B, were used to represent contrasting functional strategies, enabling the exploration of trade-offs in productivity and stability under different climate conditions. The increase in atmospheric CO_2 concentration due to climate change has a direct impact on plant physiology, by improving radiation use efficiency (RUE, g DM MJ^{-1}) (Stockle et al. 1992). The model accounts for this CO_2 fertilization effect (fCO_2) using an exponential formula derived from Stockle et al. (1992). The equation is as follows:

$$fCO_2 = 2 - \exp\left(\log\left(2 - \alpha_{CO_2}\right) \times \frac{CO_2^{atm} - 350}{600 - 350}\right) \quad (1)$$

where CO_2^{atm} (ppm) represents the atmospheric concentration of CO_2, which is provided at the same time as the other weather data. The values 350 ppm and 600 ppm are the reference concentration and the upper value used for calibration, respectively. α_{CO_2} is a parameter that controls the sensitivity of the plant to CO_2, generally around 1.2 for C3 plants, the value used in this work for both PFTs. This formulation ensures that the projections of grassland functioning account for the physiological response of C3 grasses to rising CO_2. The CO_2 values for each combination of climate model and warming scenario are shown in Table 1.

2.4.2. Site-level validation and regional-scale applicability

Gras-Sim used in this study is the same model evaluated in Kokah et al. (2023). The model was tested against multi-year observations collected at three sites distributed across contrasting agricultural regions of Wallonia: Louvain-la-Neuve (Sandy-Loamy region), Tinlot (Condroz), and Michamps (Ardennes region). These sites cover a broad range of soil depths, textures, altitudes, and climatic regimes representative of the main pedoclimatic contexts in the study area. Across sites and plant functional types, Gras-Sim simulated biomass production with a relative root mean square error (RRMSE) of 29%, a normalized deviation (ND) of 2%, and a model efficiency (EF, Nash-Sutcliffe predictive efficiency) of 0.71. For the two plant functional types, the ND values remained low (2-4%), indicating limited systematic bias. These results demonstrate that the model accurately captures biomass dynamics under contrasting water and nitrogen conditions and that its structure and parameterization remain robust across the range of pedoclimatic situations in Wallonia.

Direct validation at the pixel level is not feasible when applying the model at a regional scale and over long climatic windows. Historical yields per pixel cannot be observed across Wallonia, particularly under management conditions comparable to the standardized simulation setup. This study aims to assess the vulnerability of temperate permanent grasslands to future climate conditions by quantifying spatial and seasonal patterns of productivity and interannual stability, rather than reproducing observed regional yields under specific management regimes. To ensure consistency between the validated site-scale behavior of the model and its regional-scale application, historical simulations were aggregated by agricultural region and compared with reported regional yield ranges.

However, observed regional yield data integrate a wide range of species compositions and management practices (e.g., fertilization levels, cutting frequency, and timing) that are not explicitly represented in the standardized management assumptions used in the simulations. As a result, strict quantitative comparison is not feasible. Since the observed data are reported as ranges rather than as specific measurements, this comparison is used solely as a plausibility check to verify that simulated historical yields fall within realistic orders of magnitude at the regional scale, rather than as formal validation at the regional scale.

The simulated historical baseline primarily serves as an internally consistent reference point for assessing relative changes in productivity and stability under future climate scenarios. This approach ensures that the projected changes reflect the combined effects of climate forcing, soil heterogeneity, and functional strategies, which aligns with the core objective of the study. Aggregated regional values derived from the simulated historical data are summarized in Table S2, alongside reported regional ranges.

2.4.3. Model spatialization

Since soil and weather conditions vary spatially within the study area (Table 2), we used explicitly spatialized data. The spatialization of the Gras-Sim model was based on the interaction between the resolution of the weather data (5 km × 5 km) and that of the soil data (250 m × 250 m). Given the large number of simulations required to cover the whole of

Wallonia, the number of simulations was reduced to optimize the computation time as follows. First, the soils were classified by land use, and we retained only those corresponding to permanent grasslands, based on ISRIC data. Then, within each 5 km × 5 km climate tile, unsupervised X-means clustering (Pelleg and Moore, 2000) was performed to group soil pixels with similar characteristics and automatically determines the optimal number of clusters. Once the clusters were defined, the soil variables required for Gras-Sim (clay, sand, and soil organic matter content) were averaged by cluster. This approach balances accuracy and computational efficiency, while capturing soil-climate diversity.

Gras-Sim explicitly models coupled water and nitrogen dynamics in the soil-plant system, with these processes responding non-linearly to local pedoclimatic conditions. Key hydraulic properties such as field capacity, wilting point and saturation are determined by soil texture and organic matter content, and these properties in turn control the fraction of available water and the water stress factor. Similarly, the size and turnover of the soil organic N pool are driven by organic matter content, thereby influencing mineralization, immobilization and mineral N availability. As the growth reduction factors for water and nitrogen, as well as the soil N supply functions, rely on thresholds and non-linear responses, the model behavior cannot be reproduced using a single, region-averaged soil profile. Consequently, spatial aggregation prior to simulation would obscure critical non-linear responses to soil-climate variability.

By combining high-resolution soil data with cluster-based aggregation within each 5 km climate tile, we ensure that simulations retain the distribution of soil-climate combinations, including extreme and drought-prone soils, which have a disproportionate effect on productivity and inter-annual stability. Regional indicators (annual yield and stability) are subsequently obtained by computing the arithmetic mean of the simulated outputs across all soil-climate clusters belonging to each agricultural region. This post-simulation averaging integrates spatial heterogeneity while preserving non-linear local responses. This approach increases the robustness and representativeness of regional-scale projections while enabling synthesis at an operational scale relevant for agricultural planning.

This study was based on 10 separate sets of simulations, corresponding to the 9 combinations of the 3 climate models (CMCC-CM2-SR5, MPI-ESM1-2-HR and MIROC6) with the 3 warming scenarios (+2 °C, +3 °C and +4 °C), plus a historical scenario. Clustering reduced the total number of daily simulations by about tenfold, making the spatially explicit design computationally feasible while maintaining soil-climate heterogeneity. The resulting simulation design allowed exploration of ecological trade-offs at operationally relevant scales, without excessive computational cost. Plant parameters were held constant across all simulation zones, since Gras-Sim uses PFT-specific physiological and structural traits calibrated from experimental data (Kokah et al., 2023). The model does not explicitly simulate spatial variation in plant density; differences in productivity across regions instead arise from spatial heterogeneity in soils and climate.

2.5. Management practices

The management regime applied directly influences the model output. To focus on the effects of soil and weather conditions on grassland productivity, a standardized management scheme based on expert-input was applied consistently across all simulations. The management regime included cuts and mineral fertilization (Table 3). Cuts were triggered dynamically based on thresholds of accumulated biomass and dry spells, as detailed in Table 3. The 2 mm limit was chosen as a compromise between quantity and quality. Each cut was made at 5 cm. Nitrogen inputs were programmed early in the season and after the first two cuts. While grazing remains the dominant practice across most temperate grasslands, cutting-based management was adopted as a standardized experimental setting to isolate the effects of functional type, soil, and climate. This approach ensures tighter control of biomass dynamics and avoids variability linked to animal behavior. Such a design enables comparability across regions and scenarios.

2.6. Systemic indicators

Our study focused on two main aspects: biomass yield and stability. These indicators allow us to evaluate the productivity of grasslands under different climate scenarios and to quantify their stability in the face of climate change.

The assessment of grassland productivity is essentially based on biomass yield. This corresponds to the sum of biomass exported by the different cuts during the season, expressed in tons of dry matter per hectare (t DM ha^{-1}). Biomass production is determined by the combined influence of incident photosynthetically active radiation (PARi) and its utilization through radiation use efficiency (RUE), which is modulated by atmospheric CO_2 concentration; nitrogen inputs, which influence the ability of the plant to convert solar energy into biomass;

and cutting dates and residual heights, which condition regrowth and biomass accumulation between two cuts. Yield is therefore essential for understanding the effects of climate scenarios and for assessing how grassland productivity may respond to rising CO_2 and warming.

Production stability is a key parameter for assessing the resilience and resistance of a grassland to inter-annual weather variations and extreme events. As defined by Isbell et al. (2015), it was calculated as the ratio between the mean biomass yield (μ, t DM ha^{-1}) and its standard deviation (σ, t DM ha^{-1}) according to the following equation:

$$Stability = \frac{\mu}{\sigma} \qquad (2)$$

Since both μ and σ are expressed in the same units, stability is a dimensionless ratio. A grassland with a high but highly variable yield will have a lower stability than one with moderate but constant production. Stability is shaped by the frequency and intensity of extreme climatic events (e.g., droughts and heat waves) and by the ability of the system to recover after mowing, which depends on the cutting height and the availability of water and nitrogen. A stable ecosystem is essential to ensure regular forage production and a secure supply of biomass for livestock in a changing climate.

2.7. Statistical analysis

To ensure a precise spatial analysis, the simulation results obtained by cluster were redistributed at the pixel level, with a spatial resolution of 250 m. The statistical unit used in this study is therefore the pixel, for which annual yield (t DM ha^{-1}) and stability (μ/σ, dimensionless) variables were analyzed. This disaggregation step ensured the spatial consistency of the environmental predictors and simulation outputs. All analyses were performed for ten climate model-warming combinations (+2 °C, +3 °C and +4 °C with three climate models CMCC, MPI and MIR, plus the historical scenario). All analyses were performed in R version 4.3.3 (R Core Team, 2023), using the packages *stats* (glm), *emmeans* (pairwise comparisons), and *randomForest* (machine learning)

Given the non-normal distribution of simulation data, confirmed by Shapiro-Wilk tests, generalized linear models (GLMs) were used. Because both yield and stability were strictly positive, but showed different distributional properties, we applied a Gaussian distribution with a log link for yield since its values were approximately symmetric, whereas stability was more skewed and therefore modeled with a Gamma distribution with a log link.

GLMs were structured to test the study hypotheses, focusing on the effects of plant functional type (PFT), agricultural region, and climate model, together with continuous climatic covariates describing growing-season conditions, such as mean growing-season temperature ($\bar{T}_{gs}$), seasonal maximum daily temperature (TXx), maximum 5-day precipitation accumulation ($RX5day$), maximum number of consecutive dry days (CDD), mean growing-season rainfall ($\overline{Rain}_{gs}$), and atmospheric CO$_2$ concentration ($[CO_2]$). The final model included all two- and three-way interactions between PFT, region, and model, while the climatic covariates were included as additive effects. The management variable, number of cuts (n_{cut}), was excluded from the full GLM because it is an emergent property driven by PFT, region, climate, and model-specific harvesting rules resulting in collinearity and partial absorption of the climatic signal. Therefore, n_{cut} was evaluated separately in simplified GLMs (Eq. (S1)). The full model is written as follows:

$$\begin{aligned} Y_{ijkl} = \beta_0 &+ \beta_1 Model_i + \beta_2 PFT_j + \beta_3 Region_k + \beta_4 (Model_i \times PFT_j) \\ &+ \beta_5 (Model_i \times Region_k) + \beta_6 (PFT_j \times Region_k) \\ &+ \beta_7 (Model_i \times PFT_j \times Region_k) + \beta_8 \bar{T}_{gs} + \beta_9 TXx \\ &+ \beta_{10} RX5day + \beta_{11} CDD + \beta_{12} \overline{Rain}_{gs} + \beta_{13} [CO_2] + \varepsilon_{ijkl} \end{aligned} \tag{3}$$

where Y_{ijkl} is the response variable, $Model_i$ is the effect of climate model, PFT_j is the effect of PFT, $Region_k$ is the effect of region, β_0 is the intercept, β_n are the coefficients associated with fixed effects and interactions, and ε_{ijkl} is the residual error. The interactions between factors allowed us to quantify how functional types and regions differ in their responses to climatic conditions across models.

To identify significant differences between the levels, a pairwise comparison of the adjusted means was performed using the Tukey-Kramer method for multiple comparisons, with significance set at α = 0.05. The following equation was used:

$$\hat{\mu}_i - \hat{\mu}_j = \frac{Observed\ Difference}{Pooled\ Standard\ Error} \tag{4}$$

where $\hat{\mu}_i$ and $\hat{\mu}_j$ are the estimated means for factor levels *i* and *j*, respectively.

To assess the relative importance of the explanatory factors in predicting yield and stability, a Random Forest analysis was performed. Two separate models were fitted, one for yield and one for stability, using 500 trees per forest. The predictors were:

- climate model;
- plant functional type (PFT);
- soil properties (clay, sand, organic matter content).
- growing-season climate variables ($\bar{T}_{gs}$, TXx, $RX5day$, CDD, $\overline{Rain}_{gs}$, and $[CO_2]$)

To minimize overfitting, 10-fold cross-validation was applied, and model performance was assessed using out-of-bag (OOB) error estimate. Variable importance was quantified using two standard metrics:

- mean decrease in accuracy: the increase in prediction error when a given variable is permuted;
- mean decrease in node impurity (Gini index): The total reduction in residual sum of squares attributed to splits on each variable.

Random Forest was used as a complementary, descriptive tool to evaluate the robustness of factor importance in shaping yield and stability patterns.

3. Results

3.1. Grassland vulnerability across climate trajectories and regions

3.1.1. Context-dependent effects of climate trajectories on grasslands

Generalized linear models show that yield and stability are significantly affected by plant functional type (PFT), agricultural region, climate model, and all continuous climatic covariates including growing-season temperature, seasonal maximum temperature (TXx), maximum 5-day precipitation (RX5day), consecutive dry days (CDD), mean growing-season rainfall, and atmospheric CO_2 concentration (all $P < 0.001$; Table S3). In the following, we first describe the spatial patterns emerging from the simulations and then synthesize the dominant drivers identified by the statistical analyses. To provide a basis for interpreting these patterns, the reference biomass and stability under historical climate conditions for both PFTs A and B are illustrated in Figure S6. The significance of these climatic covariates indicates that grassland responses stem from the combined effects of various climate factors rather than from temperature alone.

The response of biomass yield to the climate trajectories associated with +2 °C, +3 °C, and +4 °C global warming varies between models. The CMCC model predicts yield declines in almost all contexts compared to historical values, spatially represented in Figure S6, particularly in areas with heavy or calcareous soils with limited drainage capacity (Grassland region, Condroz and Jurassic) for PFT A (Figure 2) and PFT B (Figure 3). In contrast, the MIR and MPI models show more heterogeneous effects. The MIR model predicts, at +2 °C, localized gains in drought-sensitive sandy soils (Hennuyere Campine, Sandy-Loamy), and fertile loams (Loamy), occasionally exceeding +2 t DM ha^{-1} (Figures 2 and 3), while the CMCC model predicts yield losses in the same contexts. At +3 °C, these contrasts become more pronounced, with the MIR and MPI models showing partial gains, particularly in calcareous uplands (Condroz), while the CMCC model continues to show a negative trend (Figures 2 and 3). At +4 °C, the trend continues; while MIR and MPI predict yield gains in almost all regions, CMCC predicts losses of up to -2 t DM ha^{-1} in clay-rich lowlands (Jurassic), particularly for PFT B (Figure 3).

Stability responses follow a similar pattern (Figures 4 and S7). The CMCC model predicts a widespread decline in stability at all warming levels, with decreases exceeding -5 at +4 °C in upland acidic soils (Ardennes), particularly for PFT A (Figure 4). In contrast, the MPI model shows moderate stability increases at +2 °C and +3 °C, particularly in fertile and calcareous systems (Grassland region and Condroz) for PFT B, before reversing at +4 °C (Figure S7). The MIR model shows localized increases of up to +5 in cooler upland sites (Ardennes and High Ardennes) at +2 °C, particularly for PFT B (Figure S7), and stability losses in calcareous uplands (Condroz and Famenne) at +3 °C and +4 °C, particularly for PFT A (Figure 4).

Full GLM outputs are provided in Tables S4 and S5. Yield increases with mean growing-season temperature ($P < 0.001$) and rainfall ($P < 0.001$) but decreases with the number of consecutive dry days ($P < 0.001$). In contrast, stability decreases with higher average growing-season temperatures ($P < 0.001$) and rainfall ($P < 0.001$). Random forest analysis confirms the dominant role of PFT as the most influential predictor of yield (importance = 135.87) and stability (importance = 95.79), followed by soil organic matter, clay, and sand (Table 4). Climatic covariates also contribute substantially, particularly mean growing-season rainfall (importance = 26.26 for stability, Table 4). These results suggest that uncertainty from climate models surpasses uncertainty from soil variability; however, soil properties and climatic covariates remain key modulators of grassland responses.

3.1.2. Regional heterogeneity in grassland vulnerability

A comparative analysis of the regions reveals significant spatial variability in grassland vulnerability, in terms of both yield and stability. The High Ardennes region has the highest average increase in yield (+2.52 ± 0.87 t DM ha^{-1} compared to the historical model), followed by the Ardennes (+2.08 ± 0.82 t DM ha^{-1}) and the Fagnes (+1.67 ± 0.90 t DM ha^{-1}) (Table 4). In contrast, the lowest average increase in yield are observed in areas with clay-limestone soils subject to drainage constraints (Jurassic, +0.87 ± 0.82 t DM ha^{-1}), more than 1.5 t DM ha^{-1} lower than in the High Ardennes region. These differences can be seen in the maps showing the absolute yield differences for functional plant types A and B (Figures 2 and 3), with the most productive areas mainly associated with cooler, high-altitude contexts (High Ardennes and Ardennes).

The ranking also reveals contrasting results for stability. The High Ardennes remained the most stable region compared to the historical model (+0.61 ± 1.64), while the Jurassic region shows the greatest instability (-2.00 ± 1.80), followed by the Famenne region (-1.46 ± 1.12) and the Loamy region (-1.24 ± 2.01) (Table 4). These results are corroborated by the stability maps (Figures 4 and S7), particularly under the CMCC +4 °C scenarios, where low-altitude areas show losses for both PFTs. In contrast, the MIR scenarios at +2 °C or +3 °C reveal pockets of maintained or even improved stability in some lowland areas (e.g. Sandy-Loamy). Some regions perform well on a single metric. Compared to the historical model, the Grassland region achieves an average yield of +1.61 ± 0.83 t DM ha^{-1} (4th out of 10 regions), but lower stability (-1.16 ± 1.08, 7th out of 10 regions) (Table 4). Similarly, although the Hennuyere Campine region was ranked 9th for yield, it was ranked 4th for stability. These discrepancies highlight that high yields do not necessarily translate into increased stability.

3.1.3. Contribution of climate extremes to grassland vulnerability

Compared to historical values, the extreme climate indices TXx (maximum daily temperature during the growing season), RX5day (maximum precipitation over five days) and CDD (number of consecutive dry days) show significant variations in several cases, depending on the climate models and the associated warming trajectory (Table 5). These changes highlight an enhanced exposure of grasslands to climate extremes, beyond mean trends. TXx increases systematically in all scenarios, indicating a clear intensification of heat waves. The highest increases are observed in the CMCC model, reaching +8.50°C, followed by the MIR and MPI models with +6.39 °C and +6.20 °C respectively, all at a global warming of +4 °C (Table 5). In Gras-Sim, these extreme conditions directly affect daily growth through temperature and water stress reduction factors, which translates climatic extremes into reduced biomass accumulation.

For RX5day, significant increases compared to historical values are observed only in the CMCC model. The CMCC model shows increases of +24.44 mm and +23.31 mm at global warming levels of +2 °C and +3 °C respectively ($P = 0.03$ and $P = 0.02$; Table 5), while the +4 °C scenario shows no significant change (+3.76 mm, $P = 0.55$) in RX5day. Despite positive mean anomalies in some scenarios (e.g. MIR at +4 °C, +12.84 mm, $P = 0.07$), neither MIR nor MPI show statistically significant changes (Table 5). In some cases, the standard deviation exceeds the mean change (e.g. RX5day in CMCC at +2 °C), indicating high interannual variability with non-significant results despite large mean values.

Meanwhile, CDD is a count-based index representing drought duration. Simulations based on the CMCC model reveal moderate but significant increases of + 4.54 days (+2 °C, $P = 0.01$), + 6.47 days (+3 °C, $P = 0.001$), and + 10.24 days (+4 °C, $P = 0.002$) (Table 5). For the MIR model, changes remain small (+1.94 to +3.61 days) and non-significant ($P = 0.07$-0.21; Table 5). MPI also shows limited changes (+1.47 to +1.84 days) with no statistical significance (Table 5). These patterns indicate a tendency toward more frequent and prolonged droughts mainly under CMCC, amplifying exposure to summer fodder shortages. Overall, depending on the model considered, the projections tend to show an intensification of the climate extremes, including heat waves, intense precipitation events, and moderate increases in drought duration, and occasional increases in heavy rainfall.

3.2. Grassland vulnerability according to plant functional type

Generalized linear models reveal that PFT significantly impacts both yield and stability ($P < 0.001$; Table S3). However, these effects do not operate uniformly across the study area. Strong interactions between PFT, agricultural region, and climate model (all $P < 0.001$; Table S3) indicate that performance contrasts between PFT A and PFT B depend strongly on pedoclimatic and climatic contexts. Consistently, across all simulations, PFT B exhibits a positive main effect on yield (β = 0.10, $P < 0.001$; Table S4), while PFT A exhibits significantly higher stability (β = −0.07, $P < 0.001$; Table S5). These results confirm the general productivity-stability trade-off between the two types. In the following, we demonstrate how this trade-off appears across different climate trajectories and regions by using a set of representative contrasts.

3.2.1. Functional type responses to projected climate trajectories

The significant interactions involving PFT demonstrate that functional differences emerge from their combined effects with climate model conditions and regional pedoclimatic contexts. Consequently, the magnitude and, in some cases, the direction of the contrast between PFT A and PFT B vary across climate models. Under the MIR model, PFT B shows higher yields than PFT A. For instance, at +4 °C global warming, the average annual yield of PFT B is 14.01 ± 0.72 t DM ha^{-1}, compared to 12.24 ± 0.40 t DM ha^{-1} for PFT A (Figure 5). However, the stability value of PFT B is lower than that of PFT A for the same model. For instance, the average stability value is 11.08 ± 1.38 for PFT A and 10.18 ± 1.30 for PFT B at +4 °C (Figure 5). Under the CMCC model, PFT B yields are higher than those of PFT A at all levels of warming. For instance, at +4 °C, the average annual yield is 11.85 ± 0.62 t DM ha^{-1} for PFT B, compared to 10.84 ± 0.58 t DM ha^{-1} for PFT A (Figure 5). In contrast, stability is slightly lower overall for PFT B (6.63 ± 0.86 versus 7.26 ± 1.10 at +4 °C, Figure 5). Under the MPI model, PFT B shows higher average annual yields, but PFT A shows the best stability (Figure 5). For instance, at +4 °C, the average annual yield was 12.93 ± 0.78 t DM ha^{-1} for PFT B compared to 11.81 ± 0.47 t DM ha^{-1} for PFT A, while stability is slightly more favorable for PFT A (8.66 ± 1.72 versus 7.48 ± 1.22, Figure 5).

3.2.2. Regional modulation of functional types under climate change

Regional patterns further confirm that the differences between PFT A and PFT B are strongly context-dependent and shaped by the interaction between climate models and local pedoclimatic characteristics (PFT × Region × Model, $P < 0.001$; Table S3). Consistent with the main GLM effects (Tables S4-S5), PFT B tends to produce higher yields across regions, whereas PFT A exhibits higher or equal stability, although the magnitude of these differences varies by climatic context.

Across regions, these contrasts consistently reflect a trade-off between productivity gains under stress (PFT B) and greater inter-annual stability (PFT A), with regional pedoclimatic conditions modulating the strength of this trade-off rather than its direction. For instance, in the High Ardennes, at +2 °C under the MIR model, the average stability is 11.30 ± 1.84 for PFT A and 11.32 ± 1.45 for PFT B, while the average annual yield is 12.05 ± 0.14 DM ha^{-1} and 13.75 ± 0.25 DM ha^{-1} for PFTs A and B, respectively (Figures 6-8 and S8). In contrast, in regions with less pronounced pedoclimatic constraints, such as the Sandy-Loamy region, differences between functional types remain limited across scenarios. For instance, at +3 °C under CMCC, PFT A exhibits a stability of 7.18 ± 0.66, whereas PFT B exhibits a stability of 6.99 ± 0.54 (Figures 8 and S8).

3.3. Seasonal dynamics of grasslands in the context of climate change

In this section, the seasonal response was analyzed using total annual yield, as the aim was to characterize the overall phenological shift in the sward in response to warming. Seasonal dynamics reflect the combined behavior of co-occurring functional types. Figures S9 and S10 show the seasonal patterns for each PFT, confirming that the sward-level interpretation is consistent with PFT-specific responses. The spring increase and summer decline arise from earlier phenological development in warmer conditions combined with growth limitations driven by temperature and water in summer.

3.3.1. Intra-annual response of grasslands to temperature gradients

The shift in the seasonal distribution of grassland biomass due to climate change is characterized by increased yields in spring, a general decline in summer and contrasting responses in autumn (Figure 9 and Table 6). These patterns emerge from climate-specific combinations of temperature, extreme heat (TXx), drought intensity (CDD), and precipitation patterns (RX5day and growing-season rainfall), all of which significantly affect yield ($P < 0.001$; Tables S3-S4).

In spring, all three models show significant departures from the historical period, with consistent increases at +3 °C and +4 °C ($P < 0.001$; Table 7), while responses at +2 °C are model-dependent (Table 7). The MIR model shows the highest increases, with an average across all three warming levels of +3.54 ± 1.05 t DM ha^{-1}, followed by the MPI model (+2.06 ± 1.45 t DM ha^{-1}) and the CMCC model (+2.00 ± 1.46 t DM ha^{-1}) (Table 6). Figure 9 shows these differences in detail according to the distinct levels of warming. The largest deviation from the historical spring average, +4.48 ± 1.42 t DM ha^{-1}, is observed under the MIR model at +4 °C. Across models, spring yields at +3 °C are consistently higher than in summer and autumn (Table 7).

A widespread decline in yield is observed for all climate models in summer. Simulations reveal average losses across all warming levels of -1.75 ± 0.97 t DM ha^{-1} under the MIR model, -1.24 ± 1.10 t DM ha^{-1} under the CMCC model and -0.78 ± 0.96 t DM ha^{-1} under the MPI model (Table 6). Figure 9 illustrates this trend in more detail for the different warming levels. The largest yield loss compared to historical performance is -2.43 ± 0.22 t DM ha^{-1} registered at +4 °C under the MIR model.

Autumn yields vary more between models. Under the MIR model, the average yield for all three warming levels is stable compared to the historical average (+0.04 ± 1.10 t DM ha^{-1}), whereas MPI and CMCC show average decreases (-0.47 ± 1.24 t DM ha^{-1} and -0.56 ± 1.21 t DM ha^{-1}, respectively, Table 6). This variability is visible in Figure 9, with details according to the warming level. The largest autumn yield increase relative to the historical average (+0.86 ± 0.84 t DM ha^{-1}) is observed under the MIR model at +4 °C, while the largest decrease (-1.29 ± 0.67 t DM ha^{-1}) is observed under the MPI model at +4 °C (Table 7).

3.3.2. Emergent management responses to climate change

As cutting and fertilisation in the simulations are directly linked to biomass thresholds (Table 3), we examined how these management patterns respond to climate change. Analyses were performed at the pixel level, with each pixel corresponding to a soil-climate cluster derived from spatial aggregation. A total of 6,874 clusters were simulated for each plant functional type (PFT). Depending on the climate model and warming level (Table 1), this resulted in between 137,480 and 206,220 pixel-years. In this study, the term “pixel-year” therefore refers to one simulation year for one soil-climate cluster. Simulations based on historical data show an average of 4.06 ± 0.36 cuts per year for PFT A and 4.52 ± 0.51 cuts per year for PFT B. Across warming scenarios, the total annual number of cuts increases slightly, with model-dependent gains ranging from +0.18 to +1.25 cuts for PFT A and +0.20 to +1.25 cuts for PFT B per year (Table S6). These increases are primarily driven by enhanced spring growth. A marked seasonal redistribution of cuts emerges across all climate models (Table S6). Spring cutting frequency increases in every warming scenario, up to +1.25 cuts under MIR for PFT B at +4 °C, consistent with accelerated early-season growth. In contrast, summer cutting frequency declines across all climate models, down to -0.79 cuts under MIR at +4 °C for PFT A (Table S6). Autumn cuts remain stable or are slightly reduced, depending on the model. These patterns mirror the described spring enhancement and summer slowdown in biomass production.

A key emergent signal is the occurrence of years with no summer cut. This never occurs in the historical baseline (0% of pixel-years) but becomes increasingly common under climate change (Table 8). Depending on the climate model, the proportion of pixel-years lacking a summer cut is 0-1.5% at +2 °C, 0.3-6% at +3 °C and 3-14% at +4 °C. MIR exhibits the strongest increases, followed by CMCC, while MPI shows the lowest incidence (Table 8). These complete summer-cut failures are a clear indicator of drought conditions and help explain the observed summer productivity losses across regions. Cutting dates also shift under warming (Table S7). The first cut consistently occurs earlier across all models, by 9-24 days for PFT A and 8-31 days for PFT B, depending on the scenario. For instance, under the MIR at +4 °C, the first cut advances to day of year (DOY) 110.0 ± 11.1 for PFT A and DOY 107.6 ± 11.6 for PFT B, compared to DOY 141.7 ± 10.9 and 138.7 ± 10.9 under historical conditions. Conversely, the last cut tends to occur slightly later, particularly under MIR and MPI. For example, PFT B reaches DOY 292.1 ±16.9 under MIR +4 °C, compared to 278.6 ± 18.6 under historical conditions. This indicates an extension to the autumn growth period in certain contexts.

As fertilization is triggered by the first two cuts only (Table 3), changes in cutting patterns affect nitrogen application. Across all warming-model combinations, almost all pixel-years still reach at least two cuts (Table S6), meaning that the full set of fertilization events continues to be applied in nearly all cases. While the timing of fertilization may shift when spring growth accelerates, the number of annual fertilization events remains almost always unchanged. Even in the driest scenarios, such as MIR +4 °C where 11-14% of pixel-years lack a summer cut (Table 8), fertilization totals remain unaffected because the first and second cuts always occur before summer growth failure.

Overall, these results show that climate warming reshapes emergent management behavior primarily through seasonal redistribution of biomass production, with cutting activity increasingly concentrated in spring and weakened or suppressed during summer droughts.

3.3.3. Influence of atmospheric CO_2 concentration on cutting frequency

To explicitly assess the impact of rising atmospheric CO_2 levels on management practices, we analyzed the relationship between CO_2 concentration and the annual number of cuts across all climate model and warming combinations. Cutting frequency increased systematically with CO_2 for both plant functional types (PFTs), although the magnitude of this increase varied depending on the model used. For PFT A, the slope of this relationship ranged from 0.03 cuts per 100 ppm CO_2 under the CMCC model to 0.08 cuts per 100 ppm CO_2 under the MPI model (Table S8). For PFT B, sensitivities were stronger still, ranging from 0.02 cuts per 100 ppm CO_2 under CMCC to 0.10 cuts per 100 ppm CO_2 under MPI. All regression slopes were highly significant ($P < 0.001$; Table S8), and the narrow confidence intervals indicated robust CO_2 effects.

3.3.4. Regional variability in the seasonal response of grasslands.

In general, spring was the most productive season in all regions. Summer is consistently associated with losses, which vary based on soil and climate conditions. This highlights the strong modulation of seasonal vulnerability by pedoclimatic gradients. The High Ardennes region (cold, humid upland with shallow acidic soils) shows the most stable productivity throughout the year. It exhibits the greatest increase in yield across all models and warming levels, compared to the historical average in spring (+2.60 ± 1.51 t DM ha^{-1}), experiences the least losses in summer (-0.93 ± 0.99 t DM ha^{-1}) and records the only positive difference in autumn yield (+0.14 ± 1.16 t DM ha^{-1}) (Table 6). This consistency reflects a mitigated seasonal response to climate change. The Ardennes region (high altitude with shallow, poorly permeable soils) shows a similar pattern, demonstrating high productivity in spring compared to the regional historical average (+2.56 ± 1.52 t DM ha^{-1}) and displaying relative resistance in summer (-0.94 ± 1.05 t DM ha^{-1}); however, a deficit is still evident in autumn (-0.14 ± 1.20 t DM ha^{-1}) (Table 6). At this level, the seasonal dynamics follow the expected pattern, with a clear increase in spring, moderate losses in summer, and partial maintenance in autumn. In contrast, the Jurassic region (clay-limestone soils prone to drainage issues) and Hennuyere Campine (sandy drought-sensitive soil) experience significant summer losses of up to -1.46 ± 1.15 t DM ha^{-1} in Hennuyere Campine (Table 6), as well as low autumn yields compared to historical averages. Losses reach nearly one ton of dry matter per hectare in the Jurassic region

(Table 6). However, their spring production remains above historical averages and comparable to that of other regions.

These regional contrasts are consistent with the significant region-climate model interactions detected in the GLMs for both yield and stability (*P* < 0.001; Table S3). These interactions highlight that seasonal responses are not uniform but rather arise from the combined effects of soil properties, local climate, and model-specific climatic trajectories. The GLM coefficients reveal that increases in growing-season temperature and decreases in rainfall impact regions unequally (Tables S4-S5), reinforcing the observed spatial gradients in seasonal vulnerability.

4. Discussion

4.1. Grassland vulnerability is conditioned by pedoclimatic context

The responses of grasslands to climate change were primarily driven by the interaction between functional types, soil properties, and key climatic stressors, rather than by warming alone. Among the climatic variables, atmospheric CO_2 contributed to yield variability, with higher concentrations being associated with increased biomass production in all scenarios. Long-term field observations confirm this effect, showing a sustained increase in biomass under elevated CO_2 (Andresen et al., 2018). However, this contribution remains secondary compared to the dominant control exerted by soil water availability and climate extremes, which primarily shape grassland vulnerability patterns. The strong contrasts observed across climate models and pedoclimatic contexts further confirm that, in addition to plant functional strategies, grassland vulnerability emerges from the combined influence of soil water availability and exposure to climatic extremes.

Simulation results from the three climate models (CMCC, MIR, and MPI) highlight strong spatial heterogeneity. Compared to historical values, all models projected a general decline in stability and relatively low yield gains, especially on shallow, limestone and marly soils with low to moderate water retention capacity. Such soils are widespread across Europe, notably in calcareous grasslands of western and southern Europe (e.g., southwestern France; Maalouf et al., 2012) and consistently show reduced productivity and stability under drought (Jackson et al., 2024), decreased resilience of seed banks (Basto et al., 2018), and heightened sensitivity to climate-management interactions (Maalouf et al., 2012).

In contrast, higher-altitude and cooler areas show yield gains ranging from 2 to over 2.5 t DM ha^{-1} under MIR and MPI models compared to historical yields. However, these gains are often coupled with lower stability, particularly under the MPI model. These results highlight the role of altitude in structuring the distribution of grassland vulnerability. This aligns with findings by Wangchuk et al. (2021), who reported increased aboveground biomass in high-altitude grassland under warming, despite a decline in plant diversity. Similarly, Li et al. (2020) showed that grassland stability components, particularly resilience, increase with altitude, though this trend plateaus or reverses beyond certain elevations. However, the effectiveness of this buffering effect depends also on soil properties. High-altitude conditions only support stable production when paired with suitable soils. Altitude is therefore not an absolute protective factor, but a modulating one whose impact depends on the underlying edaphic conditions.

Climate extremes, rather than averages, are increasingly defining the boundaries of grassland systems. When compared to historical values, the three models reveal an intensification of heat waves, heavier precipitation, and prolonged droughts, especially under CMCC model. Our results show that TXx (maximum daily temperature) increases of up to +8.5 °C and CDD (consecutive dry days) increases of more than +10 days under CMCC lead to strong reductions in stability across regions, particularly on clay-rich lowlands. These results indicate that the increasing frequency and intensity of extreme climatic events strongly amplify year-to-year production variability, resulting in systematic losses of interannual stability under future climate conditions. The pronounced decline in stability simulated under the CMCC model for both PFT A and PFT B reflects the critical influence of climate extremes in shaping grassland vulnerability, rather than changes in mean growing conditions. This pattern aligns with the findings of Liu et al. (2024) who demonstrated that the increasing frequency of extreme climatic events undermines grassland aboveground net primary production stability by amplifying production variability and diminishing resilience, ultimately threatening ecosystem functioning. Furthermore, Song et al. (2023) confirmed that the cumulative effects of multiple global change drivers, including precipitation shifts and warming, systematically decrease grassland stability through species desynchronization and reduce community-level buffering capacity. Together, these mechanisms explain why stability declines more sharply than mean yield under scenarios dominated by extreme climatic variability.

European grasslands were highly vulnerable to 2018 drought, especially on sandy soils, while wetter soils provided some resistance (Buras et al., 2020; Kowalski et al., 2022). In Wallonia, similar sensitivity was observed during the summers of 2018, 2020, and 2022. Weekly field measurements conducted by the Walloon Agricultural Research Center (CRA-W) in Gembloux (deep fertile loams) and Libramont (high-altitude shallow acidic soils) showed that sward growth came to a halt during each of these years, forcing farmers to supplement grazing with conserved forage as early as mid- to-late July. For instance, in 2022, the sward height dropped below 6.6 cm on July 20 in Gembloux, marking a near-total lack of fresh forage availability and prompting the early use of winter reserves such as corn and grass silage (Decruyenaere, 2022). These observations illustrate how simulated vulnerability patterns translate into real-world management constraints in temperate grassland systems. Simulations based on future climate data can identify areas most exposed to chronic production deficits or increased instability.

These results underline that grassland vulnerability under climate change is driven less by regional boundaries than by the interplay of soils, altitude, and exposure to extremes. Identifying areas with shallow soils, sandy textures, or poor drainage is essential for anticipating production deficits or increased production instability in temperate regions. Such insights guide adaptation through agroclimatic zoning and flexible management. Simulation tools, such as Gras-Sim (Kokah et al., 2023), provide a framework to translate climate-soil interactions into practice, for instance by adjusting stocking rate, rescheduling grazing or cuts, or activating emergency irrigation.

4.2. Grassland response to climate change is shaped by dominant functional types

The hypothesis that grasslands dominated by PFT B (e.g. *Dactylis glomerata*) are more productive, while those dominated by PFT A (e.g. *Lolium perenne*) show greater interannual stability, is confirmed. Significant interactions between functional types, climate models, and regions reveal that differences in performance depend closely on soil and climate context.

The observed differences in yield between the two plant functional types can be explained by their contrasting ecophysiological strategies. Type A species, such as *Lolium perenne*, show very early phenology and high nutritional value but lower tolerance to limiting conditions. Compared to PFT A, PFT B species, such as *Dactylis glomerata*, generally exhibit later phenology and longer leaf lifespan (Cruz et al., 2010), which confers a greater capacity to sustain production under moderate climatic stress. Simulation results revealed that PFT B exhibited a significant positive main effect on yield, confirming its status as the more productive functional type across most climate trajectories. These results align with findings from Turner et al. (2012) and Reynaert et al. (2025), who observed that *Dactylis glomerata* outperformed *Lolium perenne* in terms of short-term productivity under drought, despite signs of physiological stress.

Available empirical evidence supports these projections. During the 2018 European drought, field trials performed in Belgium on fertile loams (Loamy region) showed higher productivity for cocksfoot than for perennial ryegrass, with up to 11 tons of dry matter (DM) per hectare for cocksfoot (type B) and 7 tons of DM per hectare for perennial ryegrass (type A) (Lambert et al., 2020). Complementary evidence from controlled macrocosm experiments in France further shows that cocksfoot sustains growth and recovery under extreme climatic events. This resilience is linked to its ability to accumulate and mobilize reserves in leaf meristems, a mechanism not observed in more sensitive grasses (Volaire et al., 2020). These convergent results highlight that the contrasts captured by simulations reflect broader European patterns of grassland vulnerability, rather than local particularities.

However, these productivity gains were accompanied by lower stability. Our simulations show that PFT A has significantly higher stability than PFT B. In most simulated scenarios, Type A exhibited greater consistency in production over time than Type B, indicating that *Lolium perenne* maintains stable productivity under variable weather conditions (Turner et al., 2012). This stability, however, does not extend to severe or prolonged droughts, where ryegrass suffers strong losses and poor persistence, while cocksfoot shows greater resilience through carbohydrate reserve mobilization and microclimate buffering (Volaire et al., 2020; Reynaert et al., 2025). The stability of PFT A species is therefore relative, depending strongly on soil properties, with poor recovery on shallow soils but better persistence on organic-rich soils (Buttler et al., 2019). An approach based on functional complementarity appears more promising than exclusive specialization to ensure stable productivity. Simulation frameworks can be mobilized to explore species mixtures and identify proportions best adapted to each pedoclimatic gradient. At the European scale, advisory networks could mobilize such approaches to guide farmers in adapting their management practices. Strengthening synergies between agricultural research institutes, universities, and experimental platforms would better integrate these issues into the agricultural innovation chain.

4.3. Climate change reshapes the seasonal growth of permanent grasslands

Overall, results confirm the hypothesis that climate change will lead to a seasonal redistribution of grassland productivity, with increased growth in spring but significant summer declines compared to historical values. This is confirmed across all climate models at higher warming levels, while responses at +2 °C remain model-dependent. Autumn shows more variable responses depending on the model. These intra-annual dynamics align with well-established mechanisms by which plants adjust their phenology in response to rising temperatures and changing precipitation patterns. For instance, it is well documented that earlier leaf-out and delayed senescence in herbaceous plants are common responses to warming, although these trends can vary depending on ecosystem type and moisture availability (Piao et al., 2019; Huang et al., 2020). Cool-season grasses such as *Lolium perenne,* typically show earlier reproductive development under milder late-winter conditions, driven by increasing temperature and radiation during the pre-growth phase (Gilliland et al., 2025).

The increase in spring productivity, particularly under the MIR model, suggests that grasslands may increasingly concentrate their growth earlier in the year. This pattern has been confirmed by long-term simulations and observations in temperate European grasslands, where earlier onset of growth and lengthening of the growing season have led to earlier cutting dates and higher number of harvests annually, especially under intensified management (Petersen et al., 2021). Moreover, climate-driven advances in the onset of photosynthetic activity can indirectly enhance spring net primary productivity, particularly in systems where temperature is the dominant control on phenology and pre-season thermal conditions are favorable (Xue et al., 2023). However, in our simulations, the onset of the phenological phase occurs on nearly the same calendar day across climate models because Gras-Sim initiates heat-sum accumulation on a fixed day-of-year. Consequently, the model does not simulate the advance of the onset itself. Instead, higher spring productivity under warmer scenarios results from two factors: additional biomass accumulation on mild winter days when temperatures exceed the daily growth threshold and faster growth following phenology activation.

However, this early-season productivity may come at a cost if it is not matched by sufficient soil moisture availability, as it can lead to early depletion of water reserves and reduce plant resilience to subsequent summer droughts, which may ultimately limit total annual productivity (Petersen et al., 2021). All three climate models predict an overall loss in summer yield. Compared to historical levels, decreases exceeding 2 t DM ha^{-1} are predicted under the MIR model at +4 °C warming. These losses, align with the pronounced increases in CDD and TXx observed in our simulations, especially under CMCC, translate into extended periods of negligible net growth and reduced cutting frequency in summer. This pattern is consistent with projections showing a sharp intensification of drought conditions across Europe, particularly in summer, where frequency and severity are expected to rise significantly under future warming scenarios (Spinoni et al., 2018). The results also show that the frequency of no-summer-cut pixel-years increases by up to 14% under MIR at +4 °C, providing a clear emergent indicator of production collapse during peak drought periods. Our simulations highlight that summer losses and autumn recovery are strongly conditioned by soil depth and water storage capacity. This pattern is consistent with remote-sensing evidence from Central Europe, where sandy soils were the most drought-sensitive and wetter soils more resistant (Kowalski et al., 2022). At the continental scale, the 2018 drought caused unprecedented pasture losses compared to 2003, particularly in less drought-adapted regions of central and northern Europe (Buras et al., 2020).

Autumn shows greater variability. Under the MIR model at +4 °C warming, some simulations indicate increased yield relative to historical averages, while others predict a decline. Such variability aligns with the contrasting effects of warming on late-season growth. Warmer autumn temperatures can promote regrowth where moisture is available but cumulative summer drought often restricts regrowth potential, particularly in areas with shallow or poorly drained soils. This divergence reflects both the uncertainty in future autumn precipitation and the sensitivity of grasslands to factors such as early senescence and summer stress. Although a favorable regrowth window is theoretically possible, particularly under conditions of sufficient late-season rainfall and mild temperature (Ma et al., 2022), the cumulative effect of summer drought can also reduce soil moisture availability and limit autumn productivity (Wang et al., 2020). These contrasts were also observed in western Europe, for instance in Belgium during the 2018 drought, where remote-sensing indices (NDVI, NDWI) confirmed that cooler, wetter uplands buffered summer losses, while sandy lowlands were among the most affected (CRA-W, 2018).

These changes, compared to historical references, imply a revision of grassland management practices. Early spring growth could be used to advance mowing or grazing dates, and build up forage stocks, while summer losses may require reducing stocking rates, adjusting rest periods, or resorting to supplementary feeding. Simulation frameworks can support these adaptations by providing site-specific recommendations adapted to contrasting pedoclimatic zones and livestock systems.

4.4. Study limitations and future directions

The limitations of this study are related to the design of the climate scenario, the representation of grassland systems and management, and the scope of the analysis.

First, the climate input ensemble is limited to nine combinations of three levels of global warming (+2, +3, and +4 °C) and three CMIP6 global climate models (CMCC, MPI, and MIR), which are downscaled with a single regional climate model (MAR). These models were selected to represent different future scenarios (dry, intermediate, and warm-wet), but they do not capture the full range of uncertainty in CMIP6, especially regarding precipitation and climate extremes. The differences observed between the models illustrate the structural uncertainty inherent in climate projections; therefore, the simulated responses should be interpreted as representative of a limited set of contrasting yet non-exhaustive climate trajectories. Future work including a larger set of GCMs, additional warming levels, or alternative downscaling approaches would help broaden the range of possible outcomes and strengthen robustness.

Second, the results are not directly transferable due to several simplifications in the representation of grassland functioning and management. Cutting was used instead of grazing to standardize model inputs, and this choice limits the direct applicability of the results to livestock systems, as grazing remains widespread across temperate Europe. Future studies should incorporate dynamic grazing modules to better capture management decision-making and spatial heterogeneity in biomass removal. In addition, the functional composition of grasslands was simplified into plant functional types, without accounting for species mixtures or interspecific interactions that may affect productivity and stability. While this simplification is a limitation, the contrasting responses observed between PFTs highlight ecophysiological trade-offs that are directly relevant for forage breeding and management. Type B traits tend to favor productivity under stress, while type A traits enhance stability, pointing toward the value of complementarity in species mixtures. Soil properties were held constant, meaning that long-term changes in soil structure or water retention were not represented. Such slow processes may only have a delayed effect on short-term productivity, but they remain relevant for long-term resilience. The CO_2-RUE formulation used in the model follows the exponential response implemented in the STICS model (Beaudoin et al., 2023). In the current model setup, the effects of rising atmospheric CO_2 are represented primarily by increased radiation use efficiency. Actual evapotranspiration is not directly linked to CO_2 but is derived from potential evapotranspiration using K_c, a crop coefficient (AET = PET × K_c). Consequently, potential CO_2-induced reductions in stomatal conductance and transpiration, as well as the interaction between these reductions and soil water availability, are not explicitly represented and cannot be quantified using the outputs analyzed in this study. This modeling choice implies that the net effect of CO_2 on productivity under water-limited conditions may be over- or underestimated and that the interaction between CO_2 fertilization and drought stress should be interpreted cautiously. Although this approach is still widely used, it was calibrated for CO_2 concentrations up to around 600 ppm. Meta-analytical evidence indicates that C_3 plants exhibit saturating dose-response curves at elevated CO_2, with most biomass stimulation already realized near current atmospheric concentrations (Poorter et al., 2022). Therefore, simulated CO_2 fertilization effects beyond 600 ppm should be interpreted as upper-bound estimates rather than precise quantitative predictions.

Third, socioeconomic drivers and farmer decision-making processes were not included in this analysis. This reflects the diagnostic scope of the present study, focused on biophysical vulnerability rather than assessing specific adaptation strategies. Future work should therefore move toward coupling biophysical simulations with socioeconomic dimensions to better evaluate plausible response options under real-world constraints.

5. Conclusion

This study revealed that the vulnerability of temperate grasslands to climate change hinges on pedoclimatic conditions, season, and functional type of the dominant species. Type B (*Dactylis* *glomerata*) generally showed higher yields, while type A (*Lolium perenne*) exhibited better interannual stability, revealing the classic trade-off between productivity and stability. Additionally, a seasonal redistribution of biomass production was observed, with increased growth in spring and a marked decline in summer compared to historical averages, particularly in regions with shallow soils. These shifts have direct implications for the provision of ecosystem services. These results highlight the importance of mixed adaptation strategies based on functional complementarity, adjusted management practices, and spatial simulation tools, such as Gras-Sim. By integrating soil-climate interactions and functional traits, this study establishes a quantitative basis for identifying the most vulnerable regions and guiding targeted adaptations. This detailed vulnerability assessment is therefore the first step, which should be followed by exploring and testing adaptation scenarios that integrate plant diversity, flexible management practices, and technological innovations to design grassland systems that remain productive and stable under future climate change.

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Tables

Table 1. Global warming scenarios and corresponding CO_2 concentration from CMCC, MPI, and MIR climate models

Warming level (°C)	Climate model	Simulation period	Atmospheric CO_2 (ppm)
+2	CMCC	2024—2053	429
	MPI	2036—2065	545
	MIR	2045—2074	592
+3	CMCC	2048—2077	605
	MPI	2066—2095	722
	MIR	2071—2100	757
+4	CMCC	2060—2079	741
	MPI	2081—2100	1005
	MIR	2081—2100	1005

Table 2. Main pedoclimatic characteristics, land use, dominant farming systems, and forage productivity of the agricultural regions of Wallonia. UAA: Utilized Agricultural Area. Source: SPW Agriculture (2024b); Forton and Meniger (2020).

Region	Dominant soils & landform	Permanent grassland in UAA (%)	Share of forage area in UAA (%)	Dominant systems	Permanent grassland yield (t DM ha^{-1} $year^{-1}$)	Key notes
Loamy	Deep, fertile, well-drained loams	—	27	Arable >50%; mixed crops-cattle 18%	7-11	Largest region; Highest biomass potential
Condroz	Hilly; calcareous-clayey-loamy; variable depth	—	42	Arable 43%; dairy 7%	6.5-11	Heterogeneous productivity with soil deep
Famenne	Shallow, cherty, calcareous soils	61	76	Beef 36%; mixed dairy-beef 16%; dairy 10%	5-8	Productivity constrained by soil and rainfall
Ardennes	High altitude; shallow, acidic, poorly permeable	—	88	Beef 56%; mixed dairy-beef 14%	6-10	Crops rare due to soil and climate limits
High Ardennes	Coldest and wettest region	90	97	Dairy 53%	5.5-9	Summer growth limited; strong spring and autumn regrowth
Grassland Region	Rugged, heavy soils; bocage	83	—	Dairy 44%; beef 21%	6.5-11	Highly specialized grassland-based systems
Fagnes	Variable soils; frequent waterlogging	64	80	Dairy/beef/mixed 72%	4.5-7	Strong dependance on rainfall and management

Jurassic	Clay-limestone and marly soils, deep, locally wet	73	89	Beef 58%	6.5-11	Drainage strongly conditions yield
Sandy-Loamy	Sandy-loamy	—	27	Arable 50%; specialized livestock 26%	7-11	Historical dairy area; arable now dominant
Hennuyere Campine	Poor, sandy soils	32	50	Arable 50%; dairy 17%	6.5-11	Smallest region; drought-sensitive

Table 3. Seasonal management strategy for triggering grassland cuts and fertilization actions

Season	Biomass threshold (t DM ha^{-1})	Rain condition after the cut	Fertilization (kg N ha^{-1})
Spring	> 3.0	3 days < 2 mm day^{-1}	60 (before cut 1)
Summer	> 2.0	2 days < 2 mm day^{-1}	50 (5 days after cut 1)
Autumn	> 1.5	2 days < 2 mm day^{-1}	40 (5 days after cut 2)

Table 4. Random Forest predictor importance for yield and stability, including soil properties (clay, sand, organic matter), plant functional type (PFT), and climatic covariates such as mean growing-season temperature, seasonal maximum temperature (TXx), maximum 5-day precipitation (RX5day), consecutive dry days (CDD), mean growing-season rainfall, and atmospheric CO_2 concentration. The table also reports the performance ranking of climate models and agricultural regions based on changes in yield and stability relative to the historical baseline.

Category	Type	Group	Importance (%)		Δ Yield (t DM ha^{-1})	Δ Stability (μ/σ, dimensionless)	Yield rank	Stability rank
			Yield	Stability				
Random Forest	—	PFT	135.87	95.79	—	—	—	—
		Organic matter	86.05	90.25	—	—	—	—
		Clay	72.08	75.22	—	—	—	—
		Sand	70.03	84.29	—	—	—	—
		Climate model	19.98	16.49	—	—	—	—
		CO_2 concentration	18.78	17.42	—	—	—	—
		Temperature	17.64	14.45	—	—	—	—
		RX5day	17.61	18.92	—	—	—	—
		CDD	16.64	17.72	—	—	—	—
		Rain	16.57	26.26	—	—	—	—
		TXx	12.64	15.76	—	—	—	—
Model ranking	Climate models	MIR	—	—	2.34 ± 0.51	0.47 ± 0.84	—	—
		MPI	—	—	1.44 ± 0.45	−0.71 ± 1.26	—	—
		CMCC	—	—	0.73 ± 0.45	−2.53 ± 0.78	—	—
Region ranking	Region	High Ardennes	—	—	2.52 ± 0.87	0.61 ± 1.64	1	1
		Ardennes	—	—	2.08 ± 0.82	−0.42 ± 1.47	2	3
		Fagnes	—	—	1.67 ± 0.90	−0.13 ± 1.63	3	2

	Grassland Region	—	—	1.61 ± 0.83	−1.16 ± 1.08	4	7
	Condroz	—	—	1.47 ± 0.83	−1.16 ± 1.44	5	6
	Famenne	—	—	1.36 ± 0.84	−1.46 ± 1.12	6	9
	Sandy Loamy	—	—	1.33 ± 0.79	−1.06 ± 2.11	7	5
	Loamy	—	—	1.27 ± 0.79	−1.24 ± 2.01	8	8
	Hennuyere Campine	—	—	1.12 ± 0.86	−0.85 ± 2.37	9	4
	Jurassic	—	—	0.87 ± 0.82	−2.00 ± 1.80	10	10

Table 5. Changes (Δ) in climatic extremes, TXx (maximum daily temperature), RX5day (maximum 5-day rainfall), and CDD (consecutive dry days), across climate models and warming levels, relative to the historical baseline. All indices were computed over the growing season (day-of-year 60 to 334)

Metric	Model	Warming level +2 °C		Warming level +3 °C		Warming level +4 °C	
		Δ ± SD	*P* value	Δ ± SD	*P* value	Δ ± SD	*P* value
TXx (°C)	CMCC	4.51 ± 2.53	< 0.001	6.16 ± 2.78	< 0.001	8.50 ± 3.14	< 0.001
	MIR	4.22 ± 1.36	< 0.001	4.92 ± 2.22	< 0.001	6.39 ± 2.11	< 0.001
	MPI	2.22 ± 2.45	< 0.001	3.14 ± 2.34	< 0.001	6.20 ± 1.89	< 0.001
CDD (day)	CMCC	4.54 ± 7.46	0.01	6.47 ± 8.21	0.001	10.24 ± 12.46	0.002
	MIR	2.54 ± 5.70	0.09	3.61 ± 9.02	0.07	1.94 ± 4.85	0.21
	MPI	1.47 ± 6.09	0.35	1.84 ± 7.41	0.30	1.79 ± 8.07	0.40
RX5day (mm)	CMCC	24.44 ± 55.82	0.03	23.31 ± 46.56	0.02	3.76 ± 19.87	0.55
	MIR	0.73 ± 21.86	0.90	3.55 ± 23.18	0.56	12.84 ± 24.07	0.07
	MPI	-2.56 ± 24.79	0.69	-2.04 ± 26.16	0.75	-9.06 ± 15.49	0.11

Table 6: Seasonal yield differences and performance ranking of climate models and agricultural regions relative to the historical baseline

Category	Type	Group	Spring		Summer		Autumn	
			Δ Yield (t DM ha^{-1})	Rank	Δ Yield (t DM ha^{-1})	Rank	Δ Yield (t DM ha^{-1})	Rank
Model ranking	Climate model	MIR	3.54 ± 1.05	1	-1.75 ± 0.97	—	0.04 ± 1.10	—
		MPI	2.06 ± 1.45	2	-0.78± 0.96	—	-0.47 ± 1.24	—
		CMCC	2.00 ± 1.46	3	-1.24 ± 1.10	—	-0.56 ± 1.21	—
Region ranking	Region	High Ardennes	2.60± 1.51	1	-0.93 ± 0.99	1	0.14 ± 1.16	1
		Ardennes	2.56 ± 1.52	3	-0.94 ± 1.05	2	-0.14 ± 1.2	2
		Fagnes	2.55 ± 1.55	6	-1.11 ± 1.09	3	-0.15 ± 1.17	3
		Grassland Region	2.48 ± 1.49	10	-1.31 ± 1.04	6	-0.36 ± 1.2	5
		Condroz	2.53 ± 1.53	8	-1.33 ± 1.07	7	-0.2 ± 1.25	4
		Famenne	2.51 ± 1.51	9	-1.28 ± 1.09	4	-0.48 ± 1.13	7
		Sandy Loamy	2.55 ± 1.55	5	-1.43 ± 1.15	8	-0.5 ± 1.18	8
		Loamy	2.56 ± 1.54	4	-1.45 ± 1.13	9	-0.38 ± 1.17	6
		Hennuyere Campine	2.57 ± 1.56	2	-1.46 ± 1.15	10	-0.54 ± 1.12	9
		Jurassic	2.54 ± 1.49	7	-1.28 ± 1.06	5	-0.97 ± 1.26	10

Table 7. Seasonal changes in grasslands yield under climate models and warming levels, relative to the historical baseline.

Model	Season	Warming level +2 °C		Warming level +3 °C		Warming level +4 °C	
		Δ ± SD (t DM ha^{-1})	*P* value	Δ ± SD (t DM ha^{-1})	*P* value	Δ ± SD (t DM ha^{-1})	*P* value
CMCC	Spring	-0.06 ± 0.07	< 0.001	3.02 ± 0.09	< 0.001	3.03 ± 0.09	< 0.001
CMCC	Summer	-0.07 ± 0.21	< 0.001	-1.80 ± 0.90	< 0.001	-1.84 ± 0.86	< 0.001
CMCC	Autumn	0.24 ± 1.37	< 0.001	-0.88 ± 0.93	< 0.001	-1.04 ± 0.85	< 0.001
MIR	Spring	3.06 ± 0.08	< 0.001	3.10 ± 0.09	< 0.001	4.48 ± 1.42	< 0.001
MIR	Summer	-1.64 ± 0.98	< 0.001	-1.52 ± 1.04	< 0.001	-2.43 ± 0.22	< 0.001
MIR	Autumn	-0.50 ± 1.02	< 0.001	-0.25 ± 0.96	< 0.001	0.86 ± 0.84	< 0.001
MPI	Spring	0.00 ± 0.10	< 0.001	3.09 ± 0.10	< 0.001	3.08 ± 0.08	< 0.001
MPI	Summer	0.14 ± 0.17	< 0.001	-1.69 ± 0.97	< 0.001	-0.80 ± 0.39	< 0.001
MPI	Autumn	0.47 ± 1.21	< 0.001	-0.59 ± 1.07	< 0.001	-1.29 ± 0.67	< 0.001

Table 8. Proportion of years without any summer cut (% of pixel-years; pixels correspond to soil-climate clusters), relative to the historical baseline

PFT	Model	Warming level +2 °C		Warming level +3 °C		Warming level +4 °C	
		Pixels-years (%)	*P* value	Pixels-years (%)	*P* value	Pixels-years (%)	*P* value
A	CMCC	0.12	< 0.001	3.23	< 0.001	7.50	< 0.001
	MIR	1.50	< 0.001	4.21	< 0.001	11.32	< 0.001
	MPI	0.00	—	1.00	< 0.001	3.41	< 0.001
B	CMCC	0.52	< 0.001	3.50	< 0.001	8.10	< 0.001
	MIR	1.20	< 0.001	6.00	< 0.001	13.83	< 0.001
	MPI	0.00	—	0.32	< 0.001	3.44	< 0.001