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Track: Climate Change

Master's Degree Thesis

Climate change effects on grassland carrying capacity

a multi-model global analysis

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Preface and acknowledgements

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Abstract

The global food system is facing the task of sustainably feeding a growing population under the effects of climate change. Amidst concerns about its environmental impact, the livestock sector plays a crucial role in addressing this challenge, serving as a vital element for the food security and economic well-being of millions. Grasslands are an essential source of forage for livestock, accounting for half of the total biomass consumed by the entire livestock industry. Currently, a considerable portion of global grasslands already suffers from degradation due to inappropriate grazing practices, and overgrazing issues are anticipated to exacerbate with increasing demand for livestock products. Consequently, the response of grasslands to climate change will determine the extent to which increasing anthropogenic pressures will impact the health of these ecosystems. This analysis combines future projections of net primary productivity from five distinct vegetation models to obtain a robust estimation of climate change effects on grasslands carrying capacity (number of grazing animals a piece of land can support). The results indicate that rising temperatures and CO_2 levels will have a generally positive effect on carrying capacity, thereby implying some opportunities to increase grazing pressures. Negative hotspots, where vegetation productivity is projected to decline, will primarily be concentrated in the Horn of Africa, Australia, Brazil, and Central America, affecting only a small fraction of the world's grasslands. However, despite this overall positive outlook, climate change will generate additional challenges due to the increasing severity, frequency and duration of extreme events. In particular, the adaptation to low-productivity years will become more challenging in most of the world’s grasslands, sometimes exacerbated by declining annual minimums. Furthermore, the inter-annual variability of carrying capacity will increase for over 70% of grasslands worldwide. This implies that the productivity of these grasslands will become more variable from year to year. Failure to effectively address these challenges through appropriate adaptation strategies may eventually offset the benefits derived from increased productivity. Moreover, considerations regarding the effects of climate change on forage quality and livestock health, may further diminish the benefits of projected productivity gains. Nevertheless, the results of this analysis provide crucial insights into future threats and opportunities for livestock production, serving as valuable tools for the development of policies aimed at preserving grassland resources in response to the growing demand for animal products.

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AGB – Aboveground biomass

AU – Animal unit

CC – Carrying capacity

CMIP – Coupled Model Intercomparison Project

GCM – General circulation model

GHG – Greenhouse gas

GI – Grazing intensity

GMAT – Global mean annual temperature

ISIMIP – Inter-Sectoral Impact Model Intercomparison Project

LUCC – Land use and cover change

MAP – Mean annual precipitation

MAT – Mean annual temperature

NPP – Net primary productivity

OGFD – Open, grass- and forb-dominated ecosystems

PUF – Proper use factor

RCP – Representative Concentration Pathway

VM – Vegetation model

WL – Warming level

1. Introduction

1.1. Context

The global food system is facing the daunting task of sustainably feeding a growing population under the effects of climate change. This necessitates a transformative shift in the entire food sector, with a focus on its resource use efficiency and on its greenhouse gas intensity.

Among the various sectors, the livestock industry will play a crucial role in this transformation. Indeed, despite being responsible for significant environmental impacts and an excessive use of natural resources, livestock plays a vital role in the food security and economic well-being of millions of people. In particular, in low-income countries it is an important source of nourishment, income, and employment, directly supporting the livelihoods of local communities.

Grasslands are an essential source of forage for livestock, supplying between 50 and 60% of the total biomass consumed by the entire industry. They are one of the most dominant land cover types, covering between 25% and 43% of land surface, and they are highly diverse ecosystems, ranging from the tropical savannahs of Central Africa to the arid steppes of Central Asia. They provide numerous ecosystem services, such as carbon storage, runoff regulation, and erosion control, and they directly support the livelihoods of 600 million smallholder farmers in low-income countries.

Despite their importance, a considerable portion of global grasslands is already in a degraded state due to inappropriate grazing practices, and overgrazing issues are expected to worsen with increasing demand for livestock-based products. At the same time, climate change poses additional challenges to grassland ecosystems, through increasing CO_2 levels, temperature changes, droughts, and altered precipitation patterns.

Understanding the response of grasslands to such climatic changes is essential to understand the possible impacts that increasing anthropogenic pressures might have on their health. Future projections of carrying capacity (number of grazing animals a piece of land can support) can serve as valuable tools to guide policymakers in making well-informed decisions regarding livestock production. It is only by implementing effective policies and adaptation strategies that we can attain sustainable food production and ensure the preservation of grassland ecosystems while meeting the demands of a growing population.

1.2. Research questions and objectives

The main goal of this analysis is to understand how grasslands ecosystems will respond to climate change. To do so, future climate projections of different general circulation models will be combined with estimated future grasslands' productivities according to multiple vegetation models. This will enable the estimation of future grassland carrying capacity on a global scale. Attention will also be paid to identification of vulnerability hotspots, representing the communities that will be most affected by such change, and to understand if new opportunities for increasing grazing pressures will emerge.

This thesis has multiple purposes. Firstly, it aims to fill the gap regarding a topic that is still not widely assessed, such as the effect of climate change on the productivity of global grasslands. Existing studies have focused on limited areas or utilized a single vegetation model, whereas this analysis intends to provide robust global estimations of climate change effects on grassland carrying capacity by incorporating a wide range of vegetation models.

Another purpose of this work is to produce an open-access dataset that could be used for food system modelling, especially for food systems optimization. By providing this dataset, the analysis aims to contribute to the development of a more efficient and sustainable food system.

Lastly, this work aims to provide policymakers with valuable information that can inform global or regional policies. Grassland carrying capacity has already been used in regional policies to determine appropriate grazing pressures. By highlighting global hotspots and opportunities, this study seeks to provide useful insights for the development of new strategies to achieve food security and improve the resilience of vulnerable communities to climate change.

1.3. Structure of the thesis

First, Section 2 provides a detailed guide to relevant literature that introduces the topic and provides an overview of the state of existing research. Subsequently, Section 3 offers a comprehensive description of the data and the methodology employed, while the outcomes of this analysis are presented in Section 4. Section 5 is dedicated to discussing these findings in depth, supported by reference to relevant literature and comparisons with other studies. Lastly, Section 6 provides concluding remarks, summarizing the key points and contributions of this work.

2. Literature review

2.1. The global livestock sector

In the next decades, the global food system is going to face the challenge of feeding sustainably a growing and more meat-consuming population under the effects of climate change. This will require a transformation of the whole food sector. In particular, in order to achieve a sustainable global food production system, notable achievements in resource use efficiency and greenhouse gases (GHGs) emissions will be needed (Herrero and Thornton, 2013).

In this transition, the livestock sector plays a key role. Indeed, while providing 33% of the proteins in human diets (Havlík et al., 2014), it is also responsible for notable environmental impacts and a significant resource use. It is the largest land use sector on Earth, occupying between 30% and 45% of the world's ice-free surface (Herrero et al., 2009; Herrero et al., 2013), and it accounts for 14.5% of all anthropogenic GHGs emissions. In addition, the sector consumes roughly one third of global cropland production and one third of freshwater resources used for agriculture (Herrero et al., 2013), and is responsible for significant amounts of soil nutrients inputs (Herrero et al., 2009). As the demand of livestock-based products is projected to significantly increase in the future, especially in developing countries (Herrero and Thornton, 2013; Michalk et al., 2019), significant achievements in the resource use efficiency and GHG emissions intensity are needed.

Despite these negative environmental impacts, livestock products play a key role in the global food system and livestock itself can be also associated to a wide variety of societal benefits. Firstly, it allows the utilization of areas that are not suitable for crop production and it can consume low-quality organic by-products that that are not suitable for human nutrition (Michalk et al., 2019; O'Mara, 2012). Moreover, livestock significantly contributes to the wellbeing of millions of people and is an essential element for the food security of many communities in low-income countries. Here, livestock is a vital source of nourishment, guaranteeing the direct access to protein-rich products, such as milk and meat (Herrero et al., 2013). It is also an important economic activity, thus being a significant source of income and employment. Moreover, it can easily provide nutrients (through manure) and traction (for ploughing and transporting goods), thus enhancing the productivities of cropping systems, and it's an important asset that vulnerable communities could sold to finance investments or use as insurance when required (Herrero et al., 2009). Lastly, livestock holds great importance for women empowerment in developing countries, as women are responsible for the majority of livestock-related tasks (e.g., managing and caring for animals).

Being a source of income for 1.3 billion of people and an essential source of nourishment for 800 million people (Herrero et al., 2013), the livestock sector cannot be excluded from the discussion on how to transform the global food sector.

The livestock sector is characterized by different systems: grazing system, where the majority of the feed is directly grazed by the animals, which can be moved throughout the year or remain in a specific area, mixed systems, where livestock's feed is based on pastures and food crops, and intensive systems, characterized by high animal densities and located near large urban centers (Figure 1). In these latter two the animals are fed with supplementary feeds, and the percentage of directly grazed forage is more limited (Herrero et al., 2013).

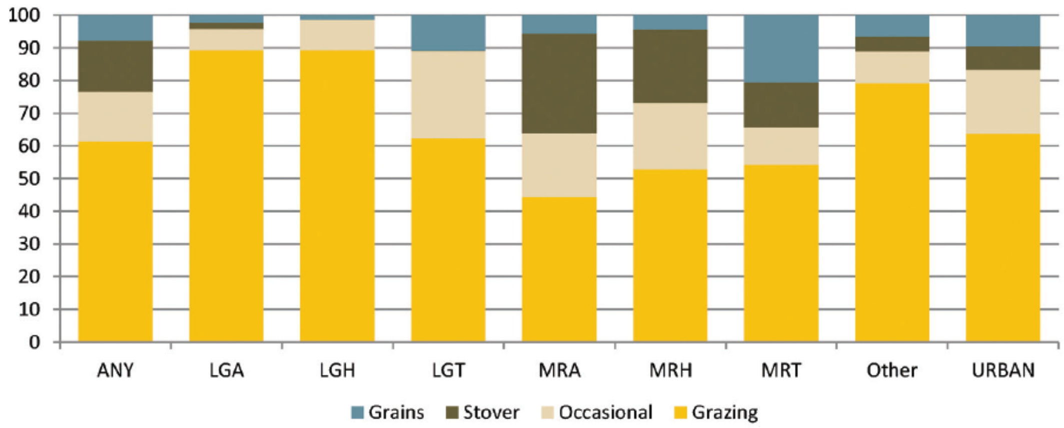

Figure 1. Average composition of global ruminant diets. LGA. livestock grazing arid; LGH, livestock grazing humid; LGT, livestock grazing temperate; MXA, mixed arid; MXH, mixed humid; MXT, mixed temperate; OTHER, other systems; URBAN, urban systems; ANY, all sytsems. Source: Havlík et al. (2015).

According to Herrero et al. (2013), mixed crop-livestock systems produce most of the meat and milk on a global level, but grazing system play a vital importance in supporting the nutritional security and incomes of the smallholder producers of Latin America, Africa, and Oceania. These latter systems usually rely on feeds of limited quality and availability, and are characterized by low productivity levels, thus lower resource efficiency and higher CO_2 emissions.

Independently of the system, grasslands are an essential source of forage, as they provide between 50% and 60% of the total global biomass consumed by livestock (Havlík et al., 2015; Herrero et al., 2013; Wolf et al., 2021). Therefore, given the predicted trends of population growth and livestock products consumption, increasing attention is now on understanding what will be the effects of such anthropogenic pressure on the health of grassland resources. The key question at hand is whether these ecosystems can accommodate a portion of the increased demand for animal-based products, particularly in regions that will face the greatest need, such as low-income countries.

2.2. Grassland ecosystems

Grassland ecosystems are an essential source of forage for livestock and they are one of the most dominant land cover types, covering between 25% and 43% of the land's ice-free surface (Gao et al., 2016b; White et al., 2000). The variability regarding their extent is related to the fact that there's no globally accepted definition of grasslands, as they generally indicate grass-dominated terrestrial ecosystems suitable for forage use (Boval and Dixon, 2012; Michalk et al., 2019; White et al., 2000). Because of this, grasslands are highly diverse ecosystems, encompassing multiple biomes and characterized by different climatic patterns, vegetation productivities, and plant species (Figure 2). Their vegetation is generally constituted by grasses, forbs, legumes, shrubs, and eventually other woody species, and they range from managed pastures, which require sowing or grazing for their maintenance, to natural ecosystems directly grazed by wildlife and livestock.

The majority of grassland resources is located in low-income countries and the largest grassland areas are found in Sub-Saharan Africa and Asia (Michalk et al., 2019). Their productivity is strictly related to the temporal and spatial patterns of temperature and precipitation, and the highest productivities are achieved in the savannas of Central and Eastern Africa, and the tropical grasslands of Eastern South America and Northern Australia (Figure 3) (Piipponen et al., 2022; Sun et al., 2021a).

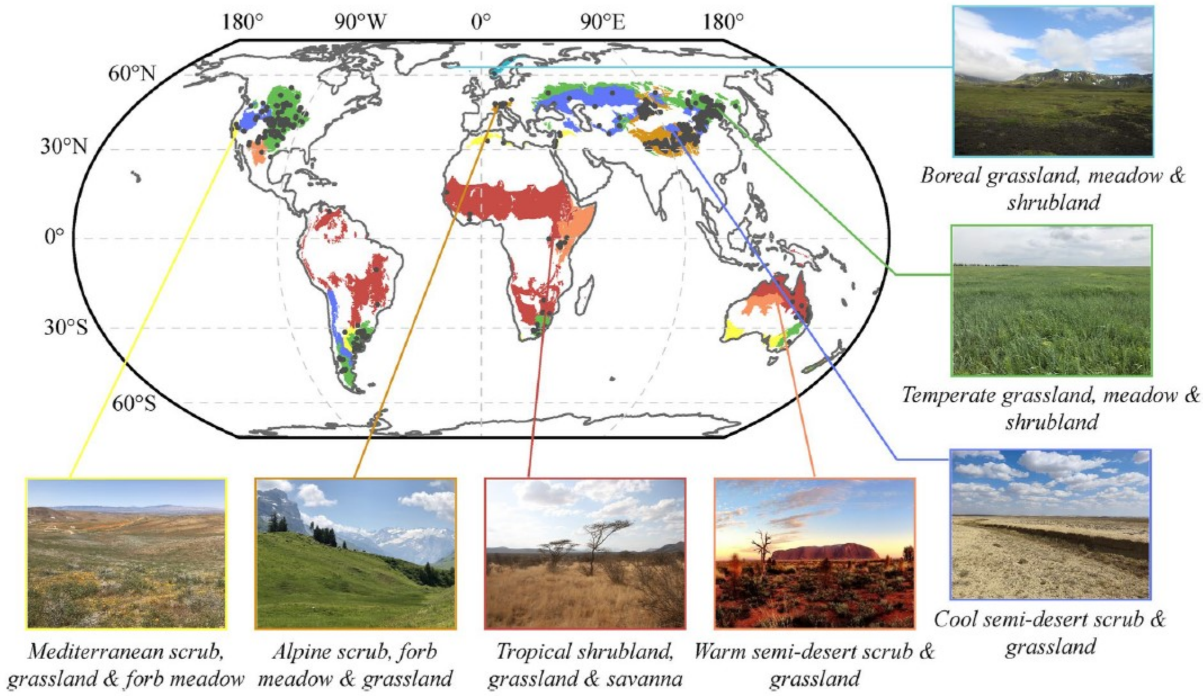

Figure 2. Different grassland ecosystems across the globe. Source: Sun et al. (2021a).

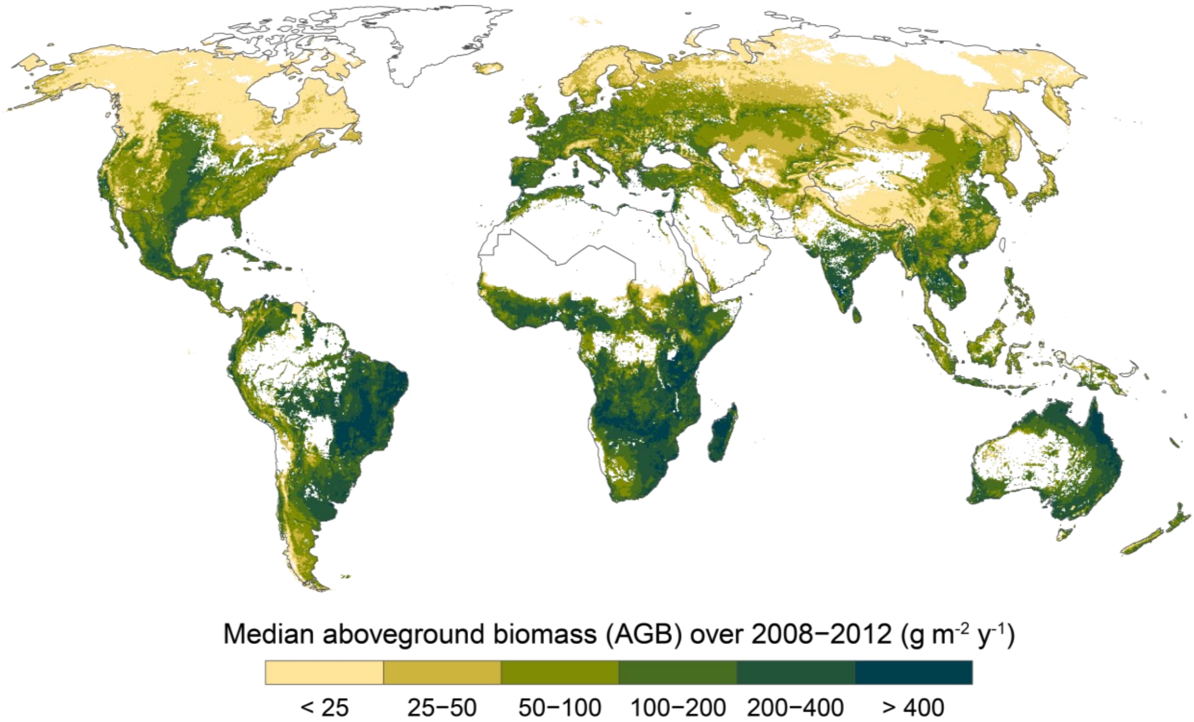

Figure 3. Productivity of grassland ecosystems across the globe expressed as aboveground biomass (biomass available for grazing). Adapted from: Piipponen et al. (2022).

Grasslands are characterized by a significant biodiversity richness and they provide several ecosystem services, such as carbon storage, runoff regulation, and erosion control (Petz et al., 2014). Indeed, as shown by Bengtsson et al. (2019), when not overgrazed, grasslands' vegetation is able to stabilize the soil and prevent surface runoff. Grasslands are also able to store in their soil significant amounts of carbon, and many consider grassland management as an effective climate change mitigation strategy (Boval and Dixon, 2012; Michalk et al., 2019; O'Mara, 2012).

In addition to these environmental benefits, grasslands directly sustain human societies, enabling the production of meat, milk, wool, and leather (White et al., 2000). They support the livelihoods of around 600 million smallholder farmers in low-income countries (Herrero et al., 2009), where the production of livestock-based products is mainly reliant on smallholder farming systems characterised by a limited resource use efficiency. Here, livestock production is closely tied to grasslands productivity, meaning that any change in grasslands' condition will significantly affect the livelihoods of millions of people. At the same time, the role of grasslands in developing countries is expected to become even more important in the future, as they will have to support an important fraction of the increased demand for livestock-based products (Boone et al., 2018; O'Mara, 2012).

In spite of this, increasing demand for animal products might undermine the health of grassland ecosystems. Indeed, despite moderate grazing intensities being related to positive effects on grasslands' condition (Bengtsson et al., 2019), the projected increasing grazing intensities are expected to exacerbate overgrazing problems (O'Mara, 2012; Petz et al., 2014). Multiple studies have shown that a considerable fraction of grasslands is already in a degraded state (Michalk et al., 2019; O'Mara, 2012; White et al., 2000), mainly due to inappropriate grazing practices, and with current approaches, an increase in the demand of animal-based products can be achieved only in spite of further degradation of grasslands. In addition to this, climate change is expected to affect the productivity and the condition of grasslands (Boone et al., 2018; Gang et al., 2017; Herrero et al., 2009), thus generating additional challenges for grasslands management.

It is therefore important to develop effective policies to define proper grazing intensities and preserve the health of global grasslands.

2.3. Grassland carrying capacity and global grazing studies

Carrying capacity (CC) is a concept developed to define proper grazing intensities and avoid land degradation. It indicates the number of grazing animals that an area can sustainably support based on its productivity (de Leeuw et al., 2019) and is expressed as number of animals per unit area and per unit time. It is estimated by evaluating the amount of available aboveground biomass (AGB) from net primary productivity (NPP) estimations, the fraction of AGB that could be sustainably grazed, and livestock's forage consumption.

However, despite being relatively simple to define and calculate, there's a limited agreement regarding its calculation principles, and different studies have adopted different methodologies to estimate grasslands CC (de Leeuw et al., 2019; Piipponen et al., 2022; Qian et al., 2012; Umuhoza et al., 2021). Indeed, some adopted a proper use factor (PUF) to express the fraction of AGB that can be sustainably grazed (de Leeuw et al., 2019), while others determined geographical restriction factors, such as for terrain slope, tree cover (Piipponen et al., 2022), or distance from water sources (Umuhoza et al., 2021), to limit AGB availability. In addition to this, the calculation of available forage is challenging and its estimations, and consequently the ones of CC and grazing intensity (GI), are highly variable in the literature. As highlighted by Fetzel et al. (2017), this is in part related to the uncertainty in NPP estimations, which can be obtained through different methods (e.g., remotely sensed data, field-based estimations, vegetation models) and which directly affect the estimations of available biomass for grazing.

In particular, when conducted on a global scale, grazing studies tend to adopt a simplified approach for the estimations of available forage. First, they usually adopt a single constant to allocate the fraction of NPP to AGB (Fetzel et al., 2017; Fetzel et al., 2017; Petz et al., 2014; Wolf et al., 2021). Moreover, they limit the spatial extent of grazing areas by excluding woody areas from the analysis (Petz et al., 2014; Wolf et al., 2021), or they consider just a constant reduction factor for tree cover (Fetzel et al., 2017).

Piipponen et al. (2022) recently developed a new methodology that enables more accurate estimations of available forage and CC. In particular, they used temperature as a proxy to allocate the fraction of NPP to AGB, similarly to other studies (de Leeuw et al., 2019; Umuhoza et al., 2021), and developed a geographical correction factor for tree cover, thus enabling the inclusion of woody areas in the analysis.

However, despite these recent improvements, global studies regarding future grasslands productivity are still very limited (Godde et al., 2020), and in general, studies on future ecosystems productivity only consider the evolution of NPP (Boone et al., 2018; Gang et al., 2017; Tian et al., 2021).

Up to date, there's no study in the literature that considers the future evolutions of grasslands CC. However, as CC estimations allow to determine proper stocking rates, ensuring sustainable grazing intensities and avoiding overgrazing, future projections of CC are an important information that could be used by policymakers to develop sustainable grazing systems. In addition, CC can be used in food system modelling and understanding its possible future trends is important to foresee the potential threats and opportunities for the production of livestock products.

2.4. Overgrazing and climate change

Despite their importance, the wealth of the world's grassland resources is constantly threatened by anthropogenic pressures. Multiple studies have shown that many grasslands are already in a degraded state (Kwon et al., 2016; O'Mara, 2012; White et al., 2000), with inappropriate stocking rates and grazing management practices being the main cause (Michalk et al. 2019). Overgrazing can lead to land degradation and desertification by decreasing soil compaction, thus enhancing soil erosion and decreasing it's runoff regulation capacity (White et al., 2000), but can also lead to plant species shift, by favoring less palatable species. Currently, 20% of global grasslands resources is in a severely degraded state (Michalk et al., 2019), and 30% of grazing land is overstocked (Piipponen et al., 2022). However, as the demand of livestock-based products is expected to increase, overgrazing issues might become even more severe and widespread in the next decades.

With that being said, the future health of grassland ecosystems will not only depend on how they will be used and managed. Indeed, as highlighted by multiple studies, climate change is also expected to significantly affect these ecosystems through increasing CO_2 levels, temperatures, drought frequency, and altered precipitation patterns (O'Mara, 2012). How grassland will respond to such changes is still unclear.

Some studies have highlighted positive impacts of historical climate change on ecosystems productivity, which globally showed an increasing trend in the last decades (Gao et al., 2022; Kolby Smith et al., 2016; Li et al., 2015). In particular, increasing temperatures and CO_2 levels have been positively correlated to NPP, because of the increased carbon accumulation rates and the lengthening of the growing season (Puche et al., 2023; Reyes-Fox et al., 2014; Tian et al., 2021). In addition, elevated CO_2 levels might even increase the resilience of grasslands to hot extremes, because of the improved water-use efficiency, and the increased root growth and nitrogen uptake during extreme events (Puche et al., 2023; Roy et al., 2016).

Given these physical responses, multiple studies agree that globally climate change could have a positive effect on ecosystems productivity also in the future (Gang et al., 2017; Tian et al., 2021). By contrast, some other studies argue that climate change might decrease the herbaceous biomass productivity of some grasslands (Godde et al., 2020; Wu et al., 2021). The same can be said for regional studies, which both predict positive effects (Gao et al., 2016a; Hufkens et al., 2016; Zarei et al., 2021) and negative ones (Qian et al., 2012). Yet, these contrasting views do not necessarily contradict each other, as the effects of climate change will vary between different grasslands of the world.

Despite this disagreement, there's a growing consensus that the projected increases in length, frequency, and severity of extreme events will affect the stability of grasslands productivity (Gao et al., 2022; Godde et al., 2020; O'Mara, 2012). In particular, Godde et al. (2020) predicted that both inter-annual (year-to-year) and intra-annual (month-to-month) variability of rangelands productivity will increase, generating additional challenges for smallholder farmers.

In spite of these emerging challenges, estimations of future grassland CC will be an essential tool to develop effective adaptation strategies to increase the resilience of vulnerable communities to climate change, achieve sustainably food security, and preserve the health of grassland ecosystems.

2.5. Vegetation models and future projections of grasslands productivity

If historical and present-day estimations of NPP can be obtained in multiple ways (e.g., field-based estimations, remotely sensed data, models simulations), the production of future projections of NPP require the use of vegetation models (VMs).

VMs simulate global vegetation patterns and try to represent the response of land ecosystems to specific climatic and other environmental conditions. They combine global climate information, provided by General Circulation Models (GCMs), with hydrological and biogeochemical cycles, land management operations and eventual disturbances (e.g., wildfires, insects damage), to simulate changes in vegetation productivity and in species abundance. These models use a limited number of plant functional types (PFTs) to represent vegetation, combining them to obtain a simplified representation of the vegetation composition of each cell according to specific ecosystems.

Up to date, a wide variety of VMs has been developed, each one with its own specific features. In particular, differences in the modelling of plant mortality, nutrients cycling, and plant competition, are some of the main sources of uncertainty in models' projections (Scheiter et al., 2013). More importantly, the lack of intercomparisons between different model results is the leading cause for significant uncertainties among future projections of ecosystems response to climate change (Tian et al., 2021).

As the few existing studies on global climate change effects on grasslands productivity are based on the result of a single VM (Boone et al., 2018; Godde et al., 2020), a more comprehensive and robust global analysis is needed. To do so, a careful analysis of the results of different VMs is required, together with a complete understanding of the differences between models and the limitations of their results.

3. Data and Methods

3.1. Methodology for carrying capacity estimations

The approach adopted to estimate carrying capacity (CC) is the one described by Piipponen et al. (2022) in their recent assessment of grassland CC through MODIS-derived data. This new methodology introduced notable improvements in CC estimations, as it developed a relationship between tree canopy cover and available biomass for grazers, allowing the inclusion of woody areas in the analysis. It also used temperature as a predictor to allocate the fraction of total net primary productivity (NPP) to aboveground biomass (AGB), instead of a single constant. This methodology has been proven to be effective also for modelled NPP estimations, producing similar results at the national and regional level (Piipponen et al., 2022, *Supporting Information*), and thus it was considered suitable for this analysis.

This approach uses total NPP to derive AGB, which is then used to estimate the CC of a specific area. NPP represents the carbon flux subtracted from the atmosphere by vegetation (g_C m^{-2}) and is obtained as the difference between gross primary productivity of photosynthesis (GPP) and plant respiration.

First, NPP is converted to total dry matter biomass (from g_C m^{-2} to $g_{Biomass}$ m^{-2}) through a carbon conversion factor. However, as plants store part of NPP below ground, this total biomass is converted to AGB, the only one available to grazers, through the factor f_{ANPP}, which represents the fraction of the NPP allocated to AGB. In this case, f_{ANPP} was calculated through the following equation (Eq. 1) developed specifically for grasslands by Sun et al. (2021b):

$$fANPP = 1 - (1.14 \times 10^{-7}\, MAP^2 - 3.07 \times 10^{-4}\, MAP - 6.65 \times 10^{-3}\, MAT + 0.786) \qquad (1)$$

where MAT represents the mean annual temperature in °C and MAP the mean annual precipitation in mm y^{-1}. This equation was considered more accurate than the one proposed by Hui and Jackson (2006) and adopted by Piipponen et al. (2022). More importantly, this relationship was assumed to be still valid under future climates. Further comments about this aspect will be made in Section 5.4.1.

The calculated AGB is then corrected for terrain slope to account for the risk of erosion and the avoidance of land degradation, and for tree canopy cover, as it has been shown that an increase in the tree canopy cover results in a non-linear reduction in the sub-canopy cover that is available to grazers (Piipponen et al., 2022).

Given what is described above, the potential biomass available for grazing in a year (AGB) is calculated through the following equation and is expressed in $kg_{Biomass}\ m^{-2}\ y^{-1}$:

$$AGB = \frac{NPP \times fANPP}{CCF} \times TCCF \times SCF \qquad (2)$$

where CCF is the carbon conversion factor ($g_{biomass}\ g_C^{-1}$), and TCCF and SCF the tree cover and slope correction factors respectively (ranging from 0 to 1).

After obtaining AGB, CC is estimated by dividing this potential available biomass by the annual forage requirement of an Animal Unit (AU), which in the literature corresponds to an animal with a weight of 455 kg and a daily forage intake varying between 1.8% and 4% of its body weight (Piipponen et al., 2022).

$$CC = \frac{AGB}{Weight_{AU} \times Daily\ Forage\ Intake \times 365} \qquad (3)$$

3.2. Datasets selection and assumptions

The methodology presented above requires consideration of six different datasets to estimate grassland CC: a land cover map to identify grassland areas, and datasets of total NPP, temperature, precipitation, tree cover, and slope correction factors. However, as this analysis has the goal of understanding the future trends of grassland CC, it is important to identify which of these datasets could change in the future and which of these changes cannot be neglected.

Of all of the different datasets, the only one that can be considered reasonably constant in the future is the terrain slope. All the others (land cover, NPP, temperature, precipitation, and tree canopy cover) are expected to change in the following decades.

A change in the future could be caused both by anthropogenic actions and climate change. As these factors are strongly interlinked, especially for land cover changes, it has been decided to maintain the current extent of grasslands adopted by Piipponen et al. (2022) for this analysis. This study therefore tries to understand the possible effects of climate change on the carrying capacity of current grassland resources. Further research could then be conducted to estimate future trends of grassland CC considering both climate change effects and anthropogenic pressures, such as land use and cover change (LUCC), or changes in fertilizers input, irrigation patterns, and land management practices.

Similarly, for the tree canopy cover correction factor it was decided to maintain the values adopted by Piipponen et al. (2022), relative to the period 2001-2015. Although forest cover is expected to be affected by climate change (Gang et al., 2017), the limitations in terms of available data forced us to make this specific assumption. However, it is still reasonable to assume that changes in tree cover will have a limited impact on the results, as the resolution of the data adopted in analysis is so coarse (30 arc/min, meaning more than 50 km at the equator) that the cells would be too big to be affected significantly by such changes. In other words, we assume that changes in tree canopy cover will occur, but that they will be very significant only at smaller scales than the resolution of the available data for future climate scenarios, thus that they would not significantly affect the value of the correction factor adopted. Further comments about the potential limitations of this approach will be made in Section 5.4.2.

Because of these assumptions, only the future projections of NPP, temperature, and precipitation were considered. The production of these projections requires the use of a Vegetation Model (VM) coupled with General Circulation Models (GCMs). However, in addition to the complexity of running a GCM and a VM, the production of robust estimations of future grassland CC requires projections from multiple model combinations (Tian et al., 2021). This is a very time-consuming task that would require enormous expertise in modelling. Therefore, it was decided to adopt the open-access datasets provided by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP).

ISIMIP is designed to "provide tailored, cross-sectorally consistent impact projections by forcing a wide range of climate-impact models with the same climate and socio-economic input and by making the data publicly available" (Frieler et al., 2017). Currently, the project has reached its third phase (ISIMIP3), which is still relatively early and so only a limited amount of available simulations results has been provided so far. For this reason, the current study is based on the data of the simulation round 2b (ISIMIP2b). This protocol was developed for the IPCC Special Report on the 1.5 °C target and is based on the future scenarios predicted by the Coupled Model Intercomparison Project phase 5 (CMIP5). These climate scenarios were adopted in the IPCC Fifth Assessment Report and they are less recent than the CMIP6 scenarios adopted in ISIMIP3 protocol (Riahi et al., 2017). However, the protocol 2b is associated with a higher data availability, providing results from multiple GCM-VM combinations and thus enabling the production of more robust analyses.

The simulation round ISIMIP2b contains the results of a wide range of climate-impact models, which are divided into different sectors. This study is based on the datasets relative to the Biomes sector, as they provide future estimations of NPP produced by different VMs.

Table 1 summarizes the original datasets adopted in this study. Further details on how they will be managed and used are given in Section 3.4.

Table 1. Datasets used in the analysis.

Data	Time interval	Resolution	Reference
Land cover type	2001-2015	5 arc-minutes	originally from Friedl and Sulla-Menashe (2022), further modified by Piipponen et al. (2022)
Tree cover correction factor	2001-2015	5 arc-minutes	originally from Sexton et al. (2013), further modified by Piipponen et al. (2022)
Slope correction factor	-	5 arc-minutes	originally from Amatulli et al. (2020), further modified by Piipponen et al. (2022)
Net primary productivity	2006-2099	30 arc-minutes	(Reyer et al., 2019)
Temperature	2006-2099	30 arc-minutes	(Lange and Büchner, 2017)
Precipitation	2006-2099	30 arc-minutes	(Lange and Büchner, 2017)

3.3. Future scenarios: data selection criteria and definition of warming levels

In this study, the effects of climate change on grassland CC will be explored by focusing on warming levels, as assessing impacts at different warming levels has been found to be beneficial for both understanding and communicating the effects of climate change. It is also considered crucial for defining effective mitigation targets and adaptation strategies (Ostberg et al., 2018).

Multiple scenarios have been developed to represent possible future climates, with the SSP-RCP scenarios being the most recent (Riahi et al., 2017). However, the ISIMIP2b simulation round is based on CMIP5 climate projections, exploring the RCP scenarios 2.6, 6.0, and 8.5. These scenarios were adopted by the IPCC in its fifth Assessment Report and represent future climatic pathways by defining a specific GHG concentration trajectory, and thus a radiative forcing trajectory (Moss et al., 2010). These trajectories are not the result of specific socioeconomic conditions and emissions scenarios but they can be associated to multiple combinations of economic, technological, and population growth. They are labelled after the possible range of radiative forcing values (W m^{-2}) reached in the year 2100.

The RCP scenario adopted in this analysis is RCP 8.5, as it is the only one able to reach multiple warming levels (WLs), namely WL1.5, WL2, WL3, which represent respectively a temperature increase of 1.5 °C, 2 °C, and 3 °C from pre-industrial levels. RCP 8.5 is an optional scenario for ISIMIP2b simulations, and this has limited the dataset selection, as not all the VMs in the Biomes sector protocol are run under this scenario.

3.3.1 ISIMIP2b datasets

As described above, the methodological approach for the estimation of climate change impacts has determined the selection of ISIMIP2b datasets adopted in the analysis.

The climate data (temperature and precipitation) adopted in this analysis represent the RCP 8.5 scenario and are presented in Table 2. These datasets are used as inputs by the different VMs adopted for the Biomes sector simulations. They are the results of 4 different GCMs of CMIP5 protocol, namely GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5. These atmospheric datasets have been already bias-adjusted for ISIMIP2b simulations with the reference dataset EWEMBI (Frieler et al., 2017).

Table 2. Temperature and precipitation datasets from ISIMIP2b used in the analysis.

Climate data	GCM	Dataset file
Temperature	GFDL-ESM2M	tas_day_GFDL-ESM2M_rcp85_r1i1p1_EWEMBI
	HadGEM2-ES	tas_day_HadGEM2-ES_rcp85_r1i1p1_EWEMBI
	IPSL-CM5A-LR	tas_day_IPSL-CM5A-LR_rcp85_r1i1p1_EWEMBI
	MIROC5	tas_day_MIROC5_rcp85_r1i1p1_EWEMBI
Precipitation	GFDL-ESM2M	pr_day_GFDL-ESM2M_rcp85_r1i1p1_EWEMBI
	HadGEM2-ES	pr_day_HadGEM2-ES_rcp85_r1i1p1_EWEMBI
	IPSL-CM5A-LR	pr_day_IPSL-CM5A-LR_rcp85_r1i1p1_EWEMBI
	MIROC5	pr_day_MIROC5_rcp85_r1i1p1_EWEMBI

Originally, the ISIMIP2b simulation round provided modelled values of global NPP from 10 different VMs. However, the models selected for the analysis were only the ones which provided results for the RCP 8.5 scenario, namely CLM4.5, LPJmL, LPJ-GUESS, ORCHIDEE, and VISIT (Table 3). All of the 5 selected models were forced by the 4 different GCMs, thus the study was based on 20 different NPP estimations (Table 4).

Table 3. Key features of the vegetation models used in the analysis.

	CLM4.5	LPJ-GUESS	LPJmL	ORCHIDEE	VISIT
Natural Vegetation Dynamics	no	yes	yes	yes	no
CO_2 fertilization effect	yes	yes	yes	yes	yes
Nitrogen limitation and cycling	yes	yes	no	no	yes
Water stress	yes	influences photosynthesis differently for each PFT	influence on photosynthesis	influences photosynthesis and phenology	influence on photosynthesis
Heat stress	no	reduction of photosynthesis at high temperatures (PFT dependent)	influence on photosynthesis	influences phenology	photosynthetic decline above optimal temperature
Drought mortality	yes	not directly, but water limitation will reduce productivity and therefore increase growth efficiency mortality	no	yes	drought affects vegetation productivity but did not increase mortality
Plant Functional Types (PFTs)	24	13	21	17	32

Table 4. Net primary productivity (NPP) datasets from ISIMIP2b used in the analysis.

VM	GCM	Dataset file
CLM45	GFDL-ESM2M	clm45_gfdl-esm2m_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	HadGEM2-ES	clm45_hadgem2-es_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	IPSL-CM5A-LR	clm45_ipsl-cm5a-lr_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	MIROC5	clm45_miroc5_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
LPJ-GUESS	GFDL-ESM2M	lpj-guess_gfdl-esm2m_ewembi_rcp85_2005soc_co2_npp-total_global_annual_2006_2099.nc4
	HadGEM2-ES	lpj-guess_hadgem2-es_ewembi_rcp85_2005soc_co2_npp-total_global_annual_2006_2099.nc4
	IPSL-CM5A-LR	lpj-guess_ipsl-cm5a-lr_ewembi_rcp85_2005soc_co2_npp-total_global_annual_2006_2099.nc4
	MIROC5	lpj-guess_miroc5_ewembi_rcp85_2005soc_co2_npp-total_global_annual_2006_2099.nc4
LPJmL	GFDL-ESM2M	lpjml_gfdl-esm2m_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	HadGEM2-ES	lpjml_hadgem2-es_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	IPSL-CM5A-LR	lpjml_ipsl-cm5a-lr_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	MIROC5	lpjml_miroc5_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
ORCHIDEE	GFDL-ESM2M	orchidee_gfdl-esm2m_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	HadGEM2-ES	orchidee_hadgem2-es_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	IPSL-CM5A-LR	orchidee_ipsl-cm5a-lr_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	MIROC5	orchidee_miroc5_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
VISIT	GFDL-ESM2M	visit_gfdl-esm2m_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	HadGEM2-ES	visit_hadgem2-es_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	IPSL-CM5A-LR	visit_ipsl-cm5a-lr_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4
	MIROC5	visit_miroc5_ewembi_rcp85_2005soc_co2_npp_global_monthly_2006_2099.nc4

ISIMIP2b simulations were conducted under different scenario designs (Frieler et al., 2017). For this analysis it was decided to use the results of simulations that assume fixed year 2005 management, land-use, irrigation patterns, and societal conditions (these simulations are indicated as "2005soc"). This allows for the separation of the effects of climate change from anthropogenic pressures, avoiding possible interactions between these two different factors.

3.3.2 Definition of warming level

The definition of warming level adopted in this study is the one used by the IPCC in its Sixth Assessment Report (Seneviratne et al., 2021). A warming level was therefore defined as "the 20-year period for which the 20-year running mean of global surface air temperature (GSAT) first exceeds a certain level of warming relative to the period 1850-1900" (Hauser et al., 2022). In this case, the reference temperature level adopted was the average global mean annual temperature (GMAT) of the decade 2006-2015, which according to the IPCC was 0.87 °C higher than 1850-1900 levels (Ipcc, 2022).

The identification of the 20-year period for a specific WL was carried out separately for each GCM, as temperature projections differ significantly between GCM even under the same RCP scenario (Tian et al., 2021). Indeed, as can be clearly observed in Figure 4, the different GCMs adopted in the analysis reach a specific WL at different time periods.

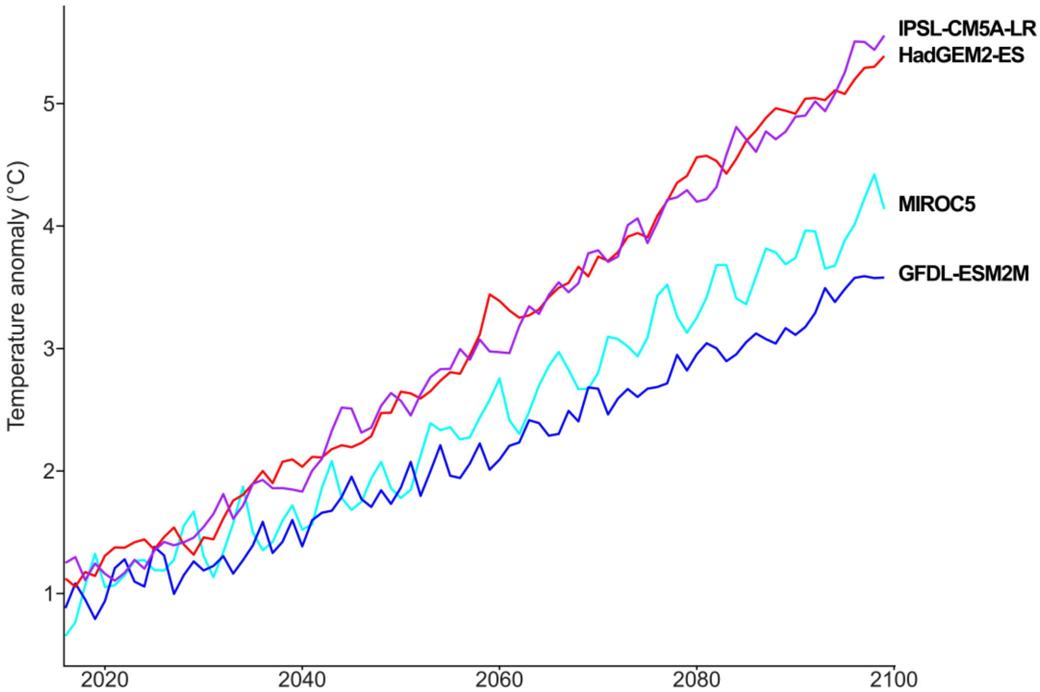

Figure 4. Temperature anomaly in respect to 1850-1900 predicted by the different general circulation models (GCMs).

This difference in the rapidity of warming affects NPP estimations and made it necessary to conduct 20 different estimations of CC for each WL. The combined results of the 20 different models combinations were then considered to assess the uncertainty of future projections.

3.4. Data processing and carrying capacity estimation

3.4.1. Pre-processing

The datasets of land cover type and correction factors (tree cover, slope) were directly retrieved from the open-access data provided by Piipponen et al. (2022). They had been already aggregated to 5 arc/min resolution and masked to the study area considered in the analysis. Their reference system was the same of ISIMIP data, thus enabling their direct utilization without any additional pre-processing.

The land cover type raster, which identifies the study area considered in this analysis, was obtained from MODIS-derived data (Friedl and Sulla-Menashe, 2022) and represents land cover classes with significant grass cover according to the IGBP (International Geosphere–Biosphere Programme) classification system, namely grasslands, savannas, and woody savannas. This study area is shown in Figure 5 with its original resolution (500 m).

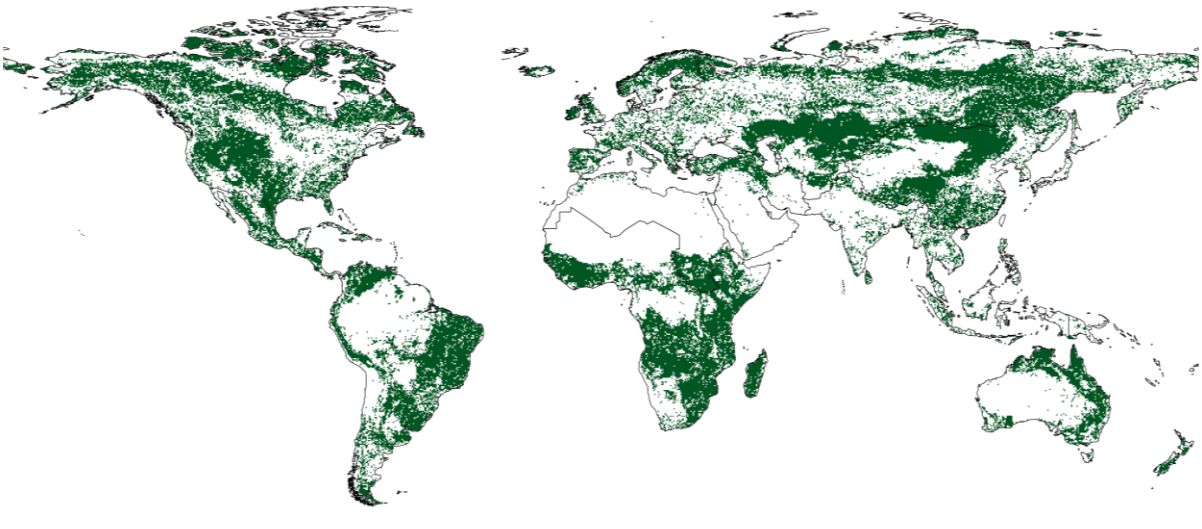

Figure 5. Study area considered in the analysis (500 m resolution).

The slope correction factor (Figure 6) was obtained from a terrain slope steepness dataset (Amatulli et al., 2020) which was reclassified following the recommendations of George and Lile (2009) shown in Table 5.

Table 5. Slope correction factor.

Slope (%)	Reduction in grazing capacity (%)
0-10	0
11-30	30
31-60	60
> 60	100

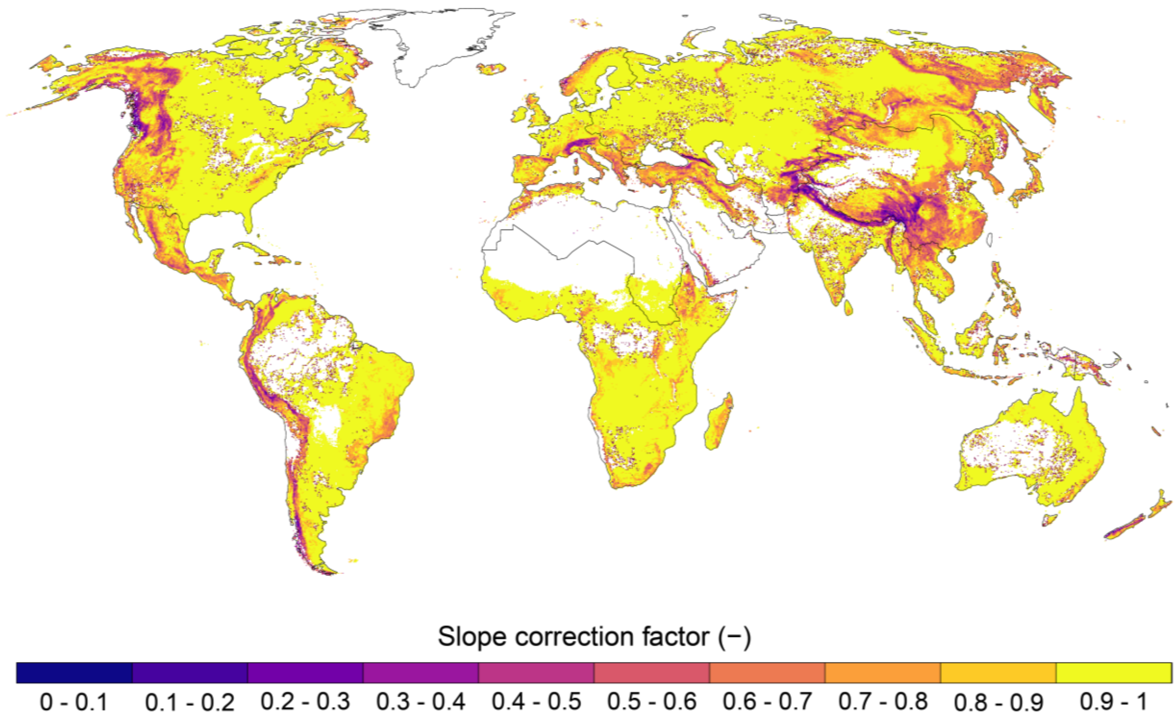

Figure 6. Slope correction factor raster adopted in the analysis. Higher values of this factor indicate a limited reduction of available biomass for grazing.

The tree cover correction factor was instead obtained from MODIS forest cover data (Sexton et al., 2013) which were reclassified with the function shown in Figure 7. Originally, the dataset had 45 different raster layers, as it contained 3 different estimations (median value and upper and lower limits of the 95% confidence interval) for every year of the period 2001-2015. However, as in this case it was not possible to consider the time variations of this factor, it was decided to adopt the mean value of all the 15 median estimations (Figure 8), thus considering it as a time-invariant factor. Further comments about the limitations of this approach will be explored in detail in Section 5.4.2.

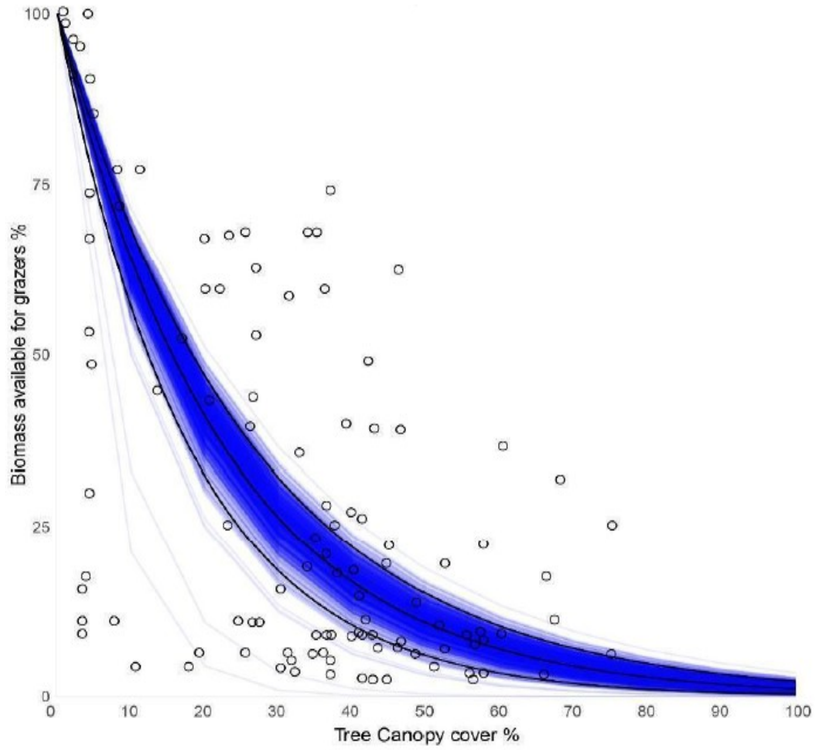

Figure 7. Function for the tree cover correction factor with 95% confidence interval. The three black lines represent the bottom, median, and top curves of the confidence interval and they were used to reclassify the forest cover datasets. Source: Piipponen et al. (2022, *Supporting Information*).

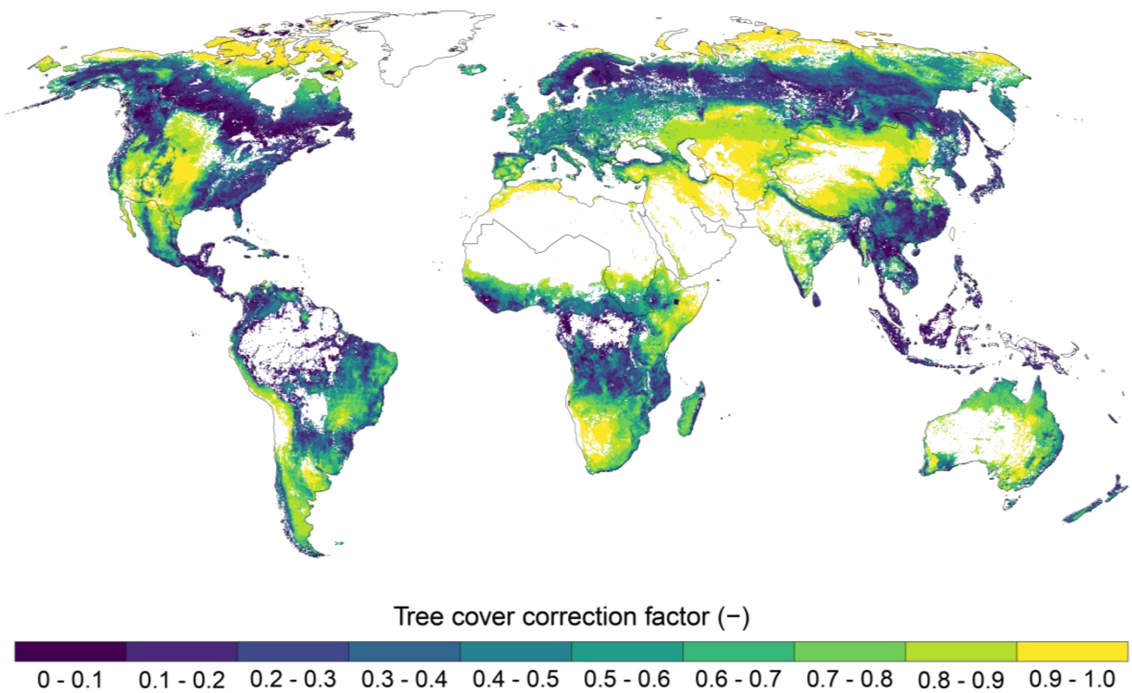

Figure 8. Tree cover correction factor raster adopted in the analysis. Higher values of this factor indicate a limited reduction of available biomass for grazing.

The ISIMIP2b datasets (NPP, temperature, precipitation) needed instead some pre-processing, in order to be converted to the correct unit and temporal resolution. Table 6 presents the details of this conversion.

Table 6. Unit and temporal resolution of original and processed ISIMIP2b datasets.

	Original dataset		**Processed dataset**	
	Temporal resolution	*Unit*	*Temporal resolution*	*Unit*
Temperature	daily	K	annual (average)	°C
Precipitation	daily	kg m^{-2} s^{-1}	annual	mm/y
NPP	daily (monthly average)	kgC m^{-2} s^{-1}	annual (average)	kgC km^{-2} y^{-1}

In addition to this, these datasets were disaggregated from 30 arc-min to 5 arc-min resolution, as the whole analysis was conducted with this latter resolution.

3.4.2. Identification of warming levels

After the gathering and eventual pre-processing of all the needed datasets, the methodological procedure explained in Section 3.3.2 was carried out to identify the time period relative to the different WLs according to each GCM. This procedure was adopted separately for each GCM, and it can be described in detail as follows. First, the GMAT was calculated for each year as a weighted average of the MAT with the grid cell area, thus obtaining a vector of 94 GMAT values (2006-2099); the baseline temperature used to calculate WLs (1850-1900) was estimated by calculating the mean value of the period 2006-2015, to which was added 0.87 °C (difference between 1850-1900 and 2006-2015); this baseline value was then subtracted to the GMAT estimations of the period 2016-2099; finally, 20-years averages for 2015-2099 were calculated and each single WL was identified by the first period in which this average was higher than a specific WL.

Table 7. 20-year periods for the warming levels considered according to the different general circulation models.

General Circulation Model	**Warming level**		
	1.5 °C	**2 °C**	**3 °C**
GFDL-ESM2M	2029-2048	2045-2064	2075-2094
HadGEM2-ES	2018-2037	2030-2049	2048-2067
IPSL-CM5A-LR	2019-2038	2030-2049	2049-2068
MIROC5	2024-2043	2040-2059	2063-2082

The 10-year time period defined above for the identification of WLs (2006-2015) was considered as a reference period to evaluate the future trends of CC under climate change scenarios. Therefore, the calculation of CC was conducted for 4 different time periods: baseline (2006-2015), and WL1.5, WL2, WL3.

3.4.3. Estimation of carrying capacity

After the identification of the 20-year time period defining each WL, 20-year annual datasets of precipitation, temperature, and NPP were produced (10-years for the baseline period). In total, 16 different temperature and precipitation datasets (4 reference time periods for 4 GCMs) and 80 NPP datasets (4 reference time periods for 20 GCM-VM combinations) were obtained. These datasets were masked to the study area defined in Figure 4 and then combined with the tree cover correction factor and slope correction factor ones according to the equation 2 presented in Section 3.1.

In addition to the rasters presented in Table 1, this methodology also requires two additional constants (carbon conversion factor and forage intake), which however showed different values in the literature. Indeed, the carbon conversion factor ranged between 0.47 and 0.50 (de Leeuw et al., 2019; Fetzel et al., 2017; Fetzel et al., 2017; Petz et al., 2014), while the daily forage intake of an AU varied between 1.8% and 4% (Piipponen et al., 2022). To account for this uncertainty and to ensure the comparability of the results, the same approach adopted by Piipponen et al. (2022) was used. More specifically, both the factors were estimated as the median value of 1000 simulations of a truncated normal distribution with a lower limit of 0.47 and an upper limit of 0.50 for the carbon conversion factor, and with 1.8%, 2%, and 4% as the lower limit, mean value, and upper limit for the forage requirement.

The procedure described above yielded for each WL and each models combination a raster of 20 layers (10 in the case of the baseline period), representing the annual CC for each year of the time period considered. The value of CC for a specific WL was then obtained by calculating the climatic average of these 20 yearly estimations.

For each WL, a number of 20 different CC estimations was obtained (as the number of models combinations), meaning 80 estimations overall for the whole analysis.

3.4.4. Estimation of inter-annual variability and negative extremes

The analysis of climatic averages provides only a partial picture of the effects that climate change will have on grassland CC. Indeed, the increasing strength, frequency, and duration of extreme events (Seneviratne et al., 2021) is expected to significantly affect also the stability of grasslands productivity and the severity of low-productivity years (Gao et al., 2022; Michalk et al., 2019; Puche et al., 2023). As these aspects could not be assessed through the analysis of climatic averages, it was decided to additionally analyse the projected trends of the coefficient of variation (CV), expressing the inter-annual (year-to-year) variability of CC, and of the minimum annual CC. They were both calculated separately from the 20 annual CC estimations for each of the different models combinations and for each specific WL.

However, the severity of low-productivity years is not only dictated by the amounts of available biomass itself but also by their difference from average conditions. Indeed, generally, livestock keepers determine the number of AUs based on average conditions, thus not being able to adapt to significant changes in biomass availability from year to year without additional feeds and efficient storage systems.

Given the above, to study the effect of climate change on the severity of low-productivity years, the following indicator was developed:

$$Negative\ Extreme\ (NE) = Average\ CC - Minimum\ CC\ [\mathrm{AU\ km^{-2}\ y^{-1}}] \quad (4)$$

where the average and minimum annual values of CC are obtained from the 20 annual CC estimations for each specific WL and models combination.

Despite not being a commonly adopted indicator, this parameter is particularly important to understand the effect of climate change on grasslands productivity. Indeed, areas showing an increasing trend of NE will indicate grasslands where the adaptation to low-productivity years will become more challenging because of climate change. In particular, a significant increase in NE could even prevent from benefitting from increased productivity.

3.4.5. Aggregation of the results at regional and national scale

In order to effectively summarize the 20 different future projections, the results obtained were aggregated at the regional and national scale (Figure 9). As CC is a density variable (AU km^{-2} y^{-1}), this was achieved by multiplying CC for the area of each cell and by summing the values of the cells relative to a specific region or nation. However, although the maps produced cover a large fraction of the globe (as they have a 5 arc-minutes resolution), the total grassland area is smaller in reality. Indeed, this is just the result of aggregation to 5 arc-minutes resolution, as the original resolution of the land cover map is 500 m. Therefore, the aggregation of the results was done by considering the fraction of grassland in each cell, which in other words represents the fraction of grassland cells with 500 m resolution in a cell with 5 arc-minutes resolution (Figure 10).

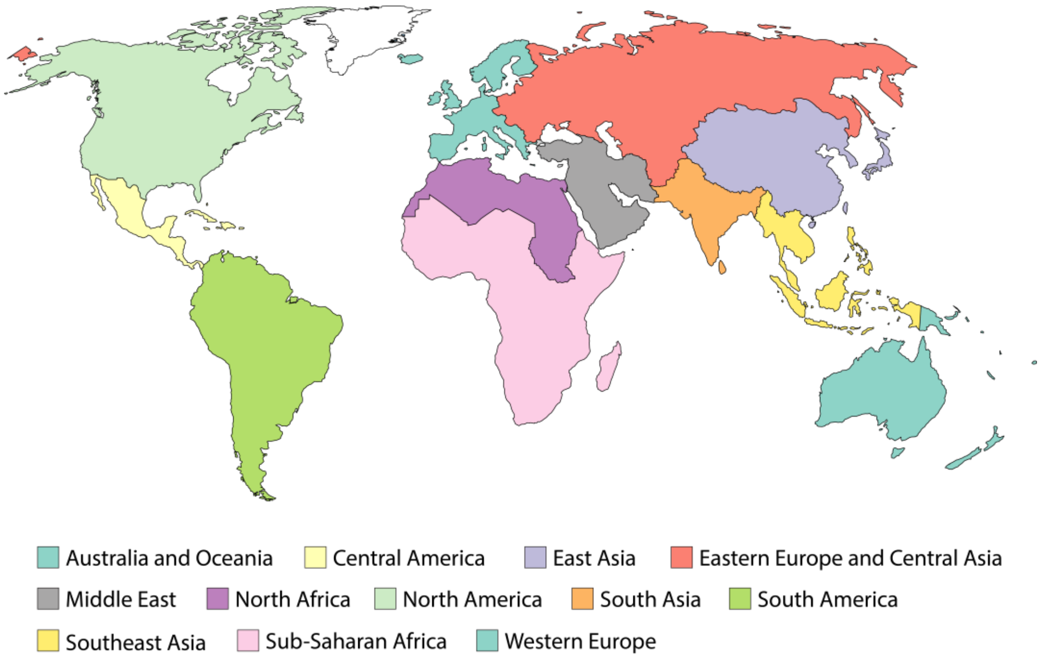

Figure 9. Regions considered for the aggregation of the results.

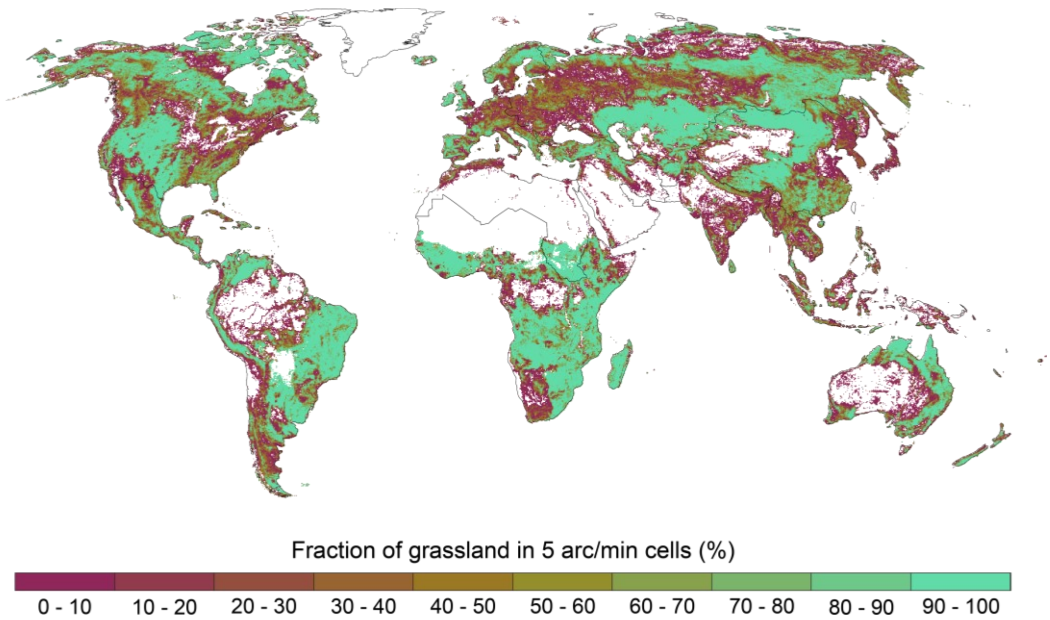

Figure 10. Fraction of grassland area in 5 arc-minutes resolution land cover map.

4. Results

4.1. Future trends of aboveground biomass and carrying capacity

Overall, climate change is expected to have a positive effect on grassland carrying capacity (CC), which is projected to increase under rising temperatures and CO_2 levels. According to the models ensemble (average of the 20 models combinations), the global annual aboveground biomass (AGB) of grasslands will increase by 7%, 13%, and 24.5% for a warming of 1.5 °C, 2 °C, and 3 °C respectively. However, the magnitude of this change is highly dependent on the rapidity of warming. Indeed, all the vegetation models (VMs) demonstrate that the increase of global AGB is more limited under rapid warming scenarios (HadGEM2-ES, IPSL-CM5A-LR) than under slower ones (GFDL-ESM2M, MIROC5). Table 8 illustrates the increases in global AGB projected by each model combination.

Table 8. Global grasslands aboveground biomass (AGB) and relative change predicted by each model combination. MODIS estimations were retrieved from Piipponen et al. (2022).

		Global aboveground biomass (Pg biomass y^{-1})				Global aboveground biomass change (%)		
Vegetation Model	**General Circulation Model**	**2006-2015**	**Warming Level 1.5 °C**	**Warming Level 2°C**	**Warming Level 3°C**	**Warming Level 1.5 °C**	**Warming Level 2°C**	**Warming Level 3°C**
CLM4.5	GFDL-ESM2M	4.92	5.13	5.31	5.64	4.3%	8.0%	14.8%
CLM4.5	HadGEM2-ES	5.06	5.26	5.35	5.61	4.0%	5.9%	11.0%
CLM4.5	IPSL-CM5A-LR	5.20	5.38	5.51	5.74	3.4%	6.0%	10.4%
CLM4.5	MIROC5	5.19	5.43	5.65	5.99	4.6%	8.7%	15.3%
LPJ-GUESS	GFDL-ESM2M	11.85	12.91	13.84	15.51	8.9%	16.8%	30.8%
LPJ-GUESS	HadGEM2-ES	12.84	13.60	14.18	15.48	5.9%	10.5%	20.6%
LPJ-GUESS	IPSL-CM5A-LR	12.17	12.95	13.59	14.70	6.5%	11.7%	20.8%
LPJ-GUESS	MIROC5	13.04	14.21	15.12	16.80	9.0%	15.9%	28.8%
LPJmL	GFDL-ESM2M	10.07	11.07	12.05	13.77	10.0%	19.7%	36.7%
LPJmL	HadGEM2-ES	10.70	11.31	11.79	12.96	5.7%	10.2%	21.2%
LPJmL	IPSL-CM5A-LR	10.02	10.68	11.17	12.20	6.6%	11.5%	21.8%
LPJmL	MIROC5	10.81	11.87	12.88	14.81	9.8%	19.1%	37.1%
ORCHIDEE	GFDL-ESM2M	10.81	12.30	13.43	15.59	13.8%	24.3%	44.2%
ORCHIDEE	HadGEM2-ES	11.45	12.46	13.16	14.63	8.8%	14.9%	27.8%
ORCHIDEE	IPSL-CM5A-LR	11.00	11.92	12.66	13.87	8.3%	15.1%	26.1%
ORCHIDEE	MIROC5	11.55	13.01	14.26	16.33	12.6%	23.5%	41.4%
VISIT	GFDL-ESM2M	10.45	11.11	11.72	13.06	6.3%	12.1%	24.9%
VISIT	HadGEM2-ES	10.97	11.48	11.82	12.61	4.6%	7.7%	14.9%
VISIT	IPSL-CM5A-LR	10.64	11.09	11.52	12.21	4.3%	8.3%	14.8%
VISIT	MIROC5	10.98	11.88	12.57	13.90	8.2%	14.4%	26.6%
Models ensemble		9.99	10.75	11.38	12.57	7.3%	13.2%	24.5%
MODIS		7.41	-	-	-	-	-	-

This expected increase in AGB, and consequently in CC, will vary markedly between different regions of the world. The biggest relative increases (%) are expected to occur in the Northern Hemisphere, in particular in North America, Eastern Europe, Central and East Asia. By contrast, a more limited relative increase in CC is expected for the grasslands of South America and Sub-Saharan Africa, where the rates of biomass productivity are already very high. Higher uncertainty between the 20 different models combinations is instead observed for the grasslands of Australia and Oceania, Central America, and North Africa. Here, the models combinations tend to disagree over future climate change effects, with multiple models agreeing that a negative trend might be observed.

These future projections are summarized by the violin plots of Figure 11. Here, the results are presented for different regions of the world as the ratio between future regional CC (average CC of the whole region) and the regional CC of the period 2006-2015, according to each model combination and for each warming level (WL) considered in the analysis. The decreasing width of the violin plots at higher levels of warming is the result of the higher uncertainty in climate projections and in the response of earth ecosystems, which could even lead to completely different pathways, as in the case of Australia and Central America.

Because of the different productivity rates among the world's grasslands (Figure 12a), the biggest absolute increases in CC (AU km^{-2} y^{-1}) are expected to occur in Uruguay, Northern Argentina, and the central grasslands of the United States, which are already very productive areas, and in the grasslands of Southern Africa and China, where this growth will be even more significant when compared to baseline levels (*Appendix - Figure 24*). At the same time, a decrease in carrying capacity is projected for multiple areas of the Brazilian plateau, Northern South America, Mexico, and the grasslands of Australia and the Horn of Africa. Figure 13 shows these changes according to the models ensemble (average of the 20 different changes for each WL).

Higher WLs were seen to be associated with higher increases of CC, with the biggest increases occurring for a warming of 3 °C. At the same time, decreasing trends are more widespread under limited levels of warming, as the strength of the CO_2 fertilization effect predicted by the models is still limited. This partially explains why some areas show an opposite trend between different WLs (negative under a warming of 1.5 °C, positive with increasing warming). Further comments about this aspect will be made in Section 5.2.4.

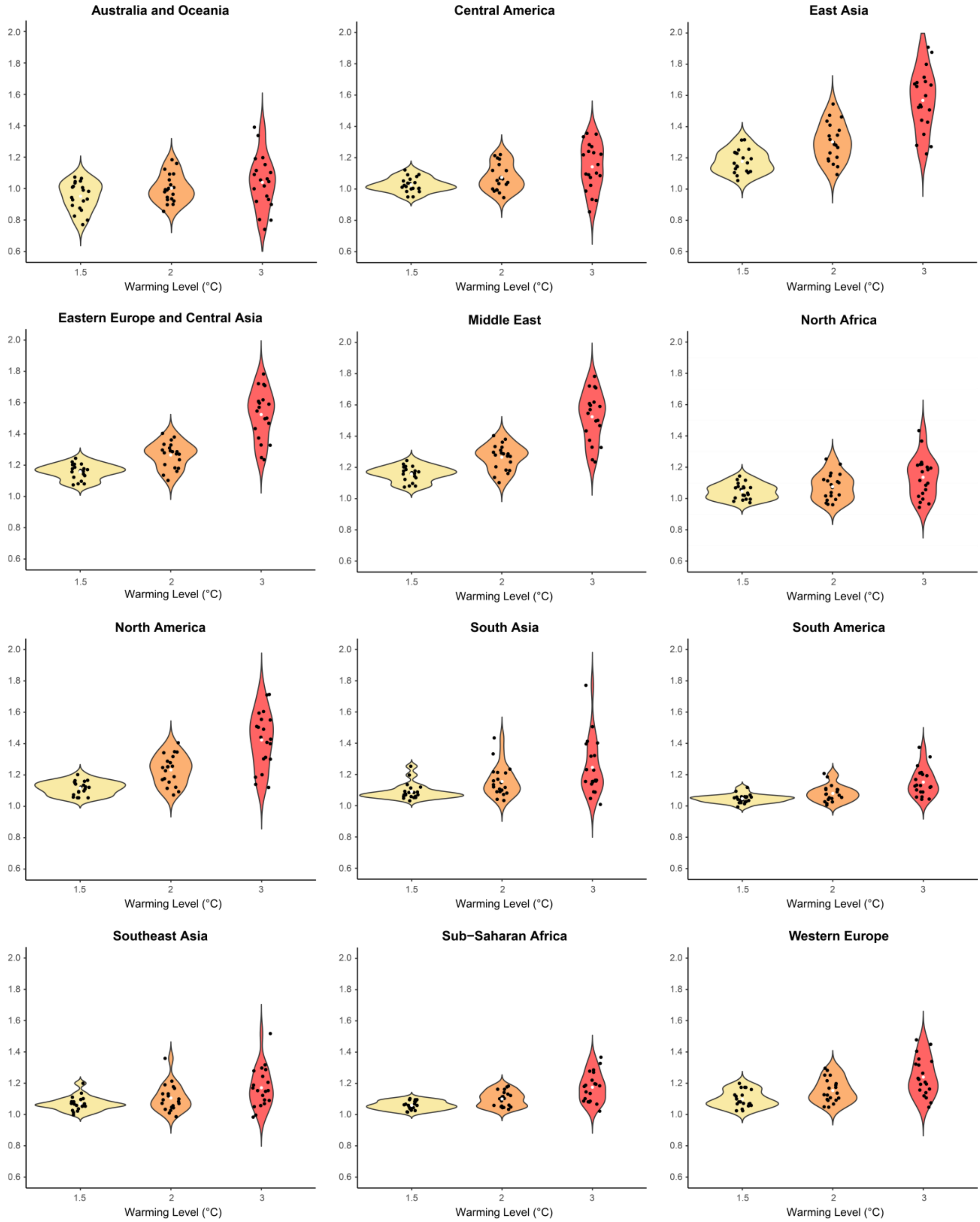

Figure 11. Violin plots for projected trends of regional carrying capacity (CC). A violin plot is a box plot with the width of the box proportional to the estimated probability density of CC estimations. The maximum density of each specific data distribution is indicated by the largest width of the violins. The black dots in the violin plots represent the results of each models combinations, while the white dot indicates their average. The y axis represents the ratio between future regional CC and the regional CC of the period 2006-2015.

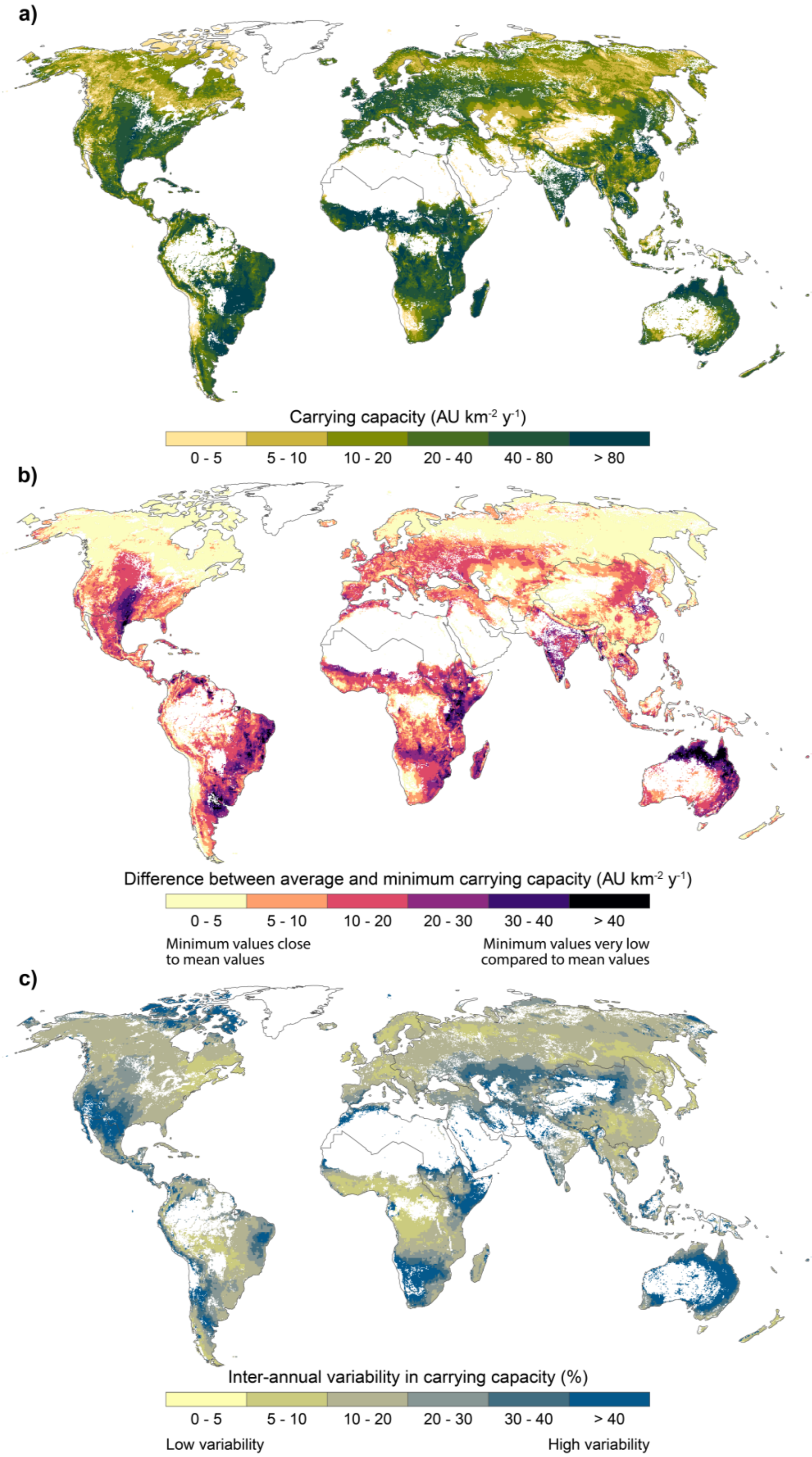

Figure 12. Carrying capacity (a), negative extremes (b), and inter-annual variability (expressed as coefficient of variation) (c) estimations for the period 2006-2015 according to the models ensemble.

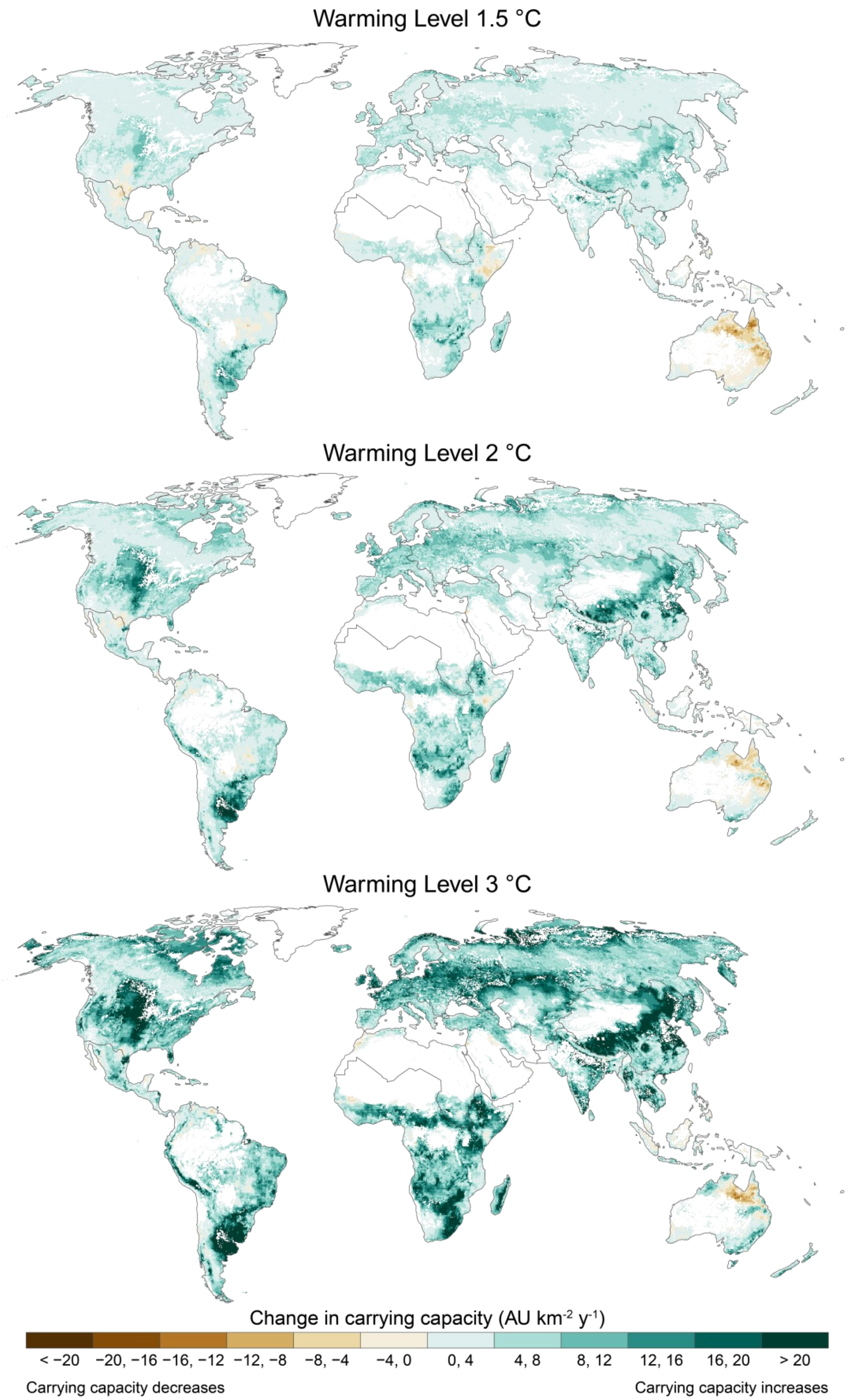

Figure 13. Absolute change of carrying capacity (AU km^{-2} y^{-1}) according to the models ensemble. Each map represents the change for future scenarios expressed as warming levels (mean over 20 years periods) from a baseline period (mean of 2006-2015).

Despite these promising benefits, the analysis of climatic averages provides only a partial picture of the effects that climate change will have on grassland CC. Indeed, while it has been shown that in general increasing temperatures and CO_2 levels will be beneficial for plant productivity, prolonged periods of high temperatures coupled with limited precipitation can instead limit biomass production, eventually leading to significantly low-productivity years.

This effect is shown in Figure 14, where an assessment on the severity of future low-productivity years is presented through the analysis of the absolute change of minimum annual CC. As can be observed, decreasing trends of minimum CC are particularly severe in great parts of the Horn of Africa, Eastern Europe, and the highly productive grasslands of the Brazilian plateau and Australia. By contrast, in areas where productivity is constrained by seasonality, the annual minimums tend to increase with increasing warming because of the longer growing season and the higher productivity in non-drought-affected months. This is the case for the grasslands of the Qinghai-Tibetan Plateau and most of the United States, Canada, Russia, and Northern Europe, where currently productivity is constrained by low temperatures (*Appendix - Figure 26*).

As shown in Figure 14, low-productivity years seem to be more severe and widespread under a warming of 1.5 °C, with minimum CC increasing in most areas of the world with increased warming. From the physical point of view, this is explained by the fact that higher WLs are associated with a higher CO_2 fertilization effect, which, according to multiple studies, improves grasslands resilience to extreme events through accelerated biomass production, improved water efficiency, and increased nitrogen uptake (Puche et al., 2023; Roy et al., 2016). From the computational point of view however, this is also a result of the temporal resolution of the analysis (annual). Indeed, as drought and heat waves usually last for less than an entire year, the heat-stress-related declines in productivity induced by dry periods can be partially or totally compensated for by the increased productivity during the rest of the year, as already shown by Hufkens et al. (2016).

However, as discussed in Section 3.4.4, the severity of low-productivity years is not only determined by the levels of minimum CC, but also by their difference from average conditions. In particular, increasing differences between average biomass availability and low-productivity years could significantly affect the livelihood of livestock keepers, especially in areas with a limited adaptive capacity.

As shown in Figure 15, the adaptation to these low-productivity years is projected to become more challenging under a changing climate and in some nations it could even offset the benefits of increased productivity (*Appendix - Figure 25, Figure* 27). Overall, the models combinations agree on a worldwide increase in NE, with significant changes occurring already under a global warming of 1.5 °C. Higher warming corresponds, then, to a high degree of change, becoming significantly more severe in a 3 °C hotter climate. Increases in the difference between average and minimum CC are projected to be particularly severe in the Horn of Africa, where these differences are already very significant (Figure 12b), and for the grasslands of Europe, southern United States, and Brazil. NE is projected to decrease only in some parts of Australia, where low-productivity years are already highly severe and CC is expected to decrease.

It is of particular interest to understand the reasons for these future trends, as they are the result of different conditions. Indeed, the increases in NE in the grasslands of the United States are mainly due to the significant increases in average productivity levels, while for the Horn of Africa they are the result of combined increased average productivity and severity of low-productivity years. As regards the greater part of the Brazilian grasslands, where differences between average and minimum annual CC are more moderate, the projected increase in NE is mainly related to the increasing severity of low-productivity years.

At the same time, the increasing strength, frequency, and duration of extreme events is going to affect not only the productivity of grasslands, but also its stability. Indeed, the analysis of the coefficient of variation (CV) of CC showed that the inter-annual variability of grasslands CC is expected to increase in multiple grasslands of the world (Figure 16). This means that CC is projected to become more variable from year to year, thus posing additional challenges to smallholder farmers. The effects of extreme events will be particularly severe in areas where inter-annual variability is already high (Figure 12c), such as the Horn of Africa, Southern Africa, part of the Sahel Region, Kazakhstan, Southern United States, and Mexico, and also for areas where currently CC is more stable, like the whole Europe. At the same time, climate change is expected to have a positive effect on the stability of the CC of the grasslands of the Qinghai-Tibetan Plateau, Northern Argentina, Eastern Brazil, and Western United States. Here, annual values of grassland CC will become more similar from year-to-year.

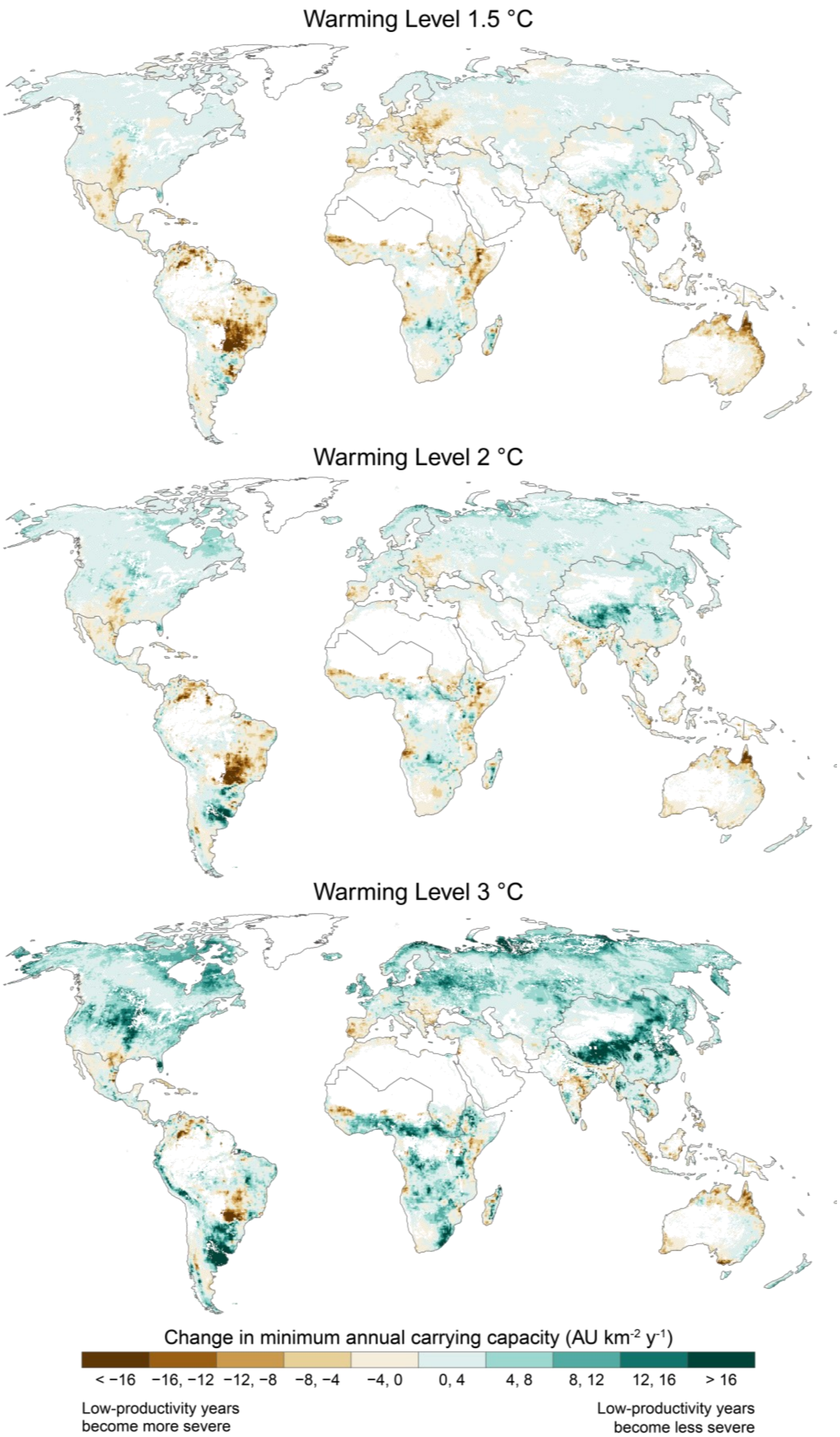

Figure 14. Absolute change of minimum annual carrying capacity (AU km^{-2} y^{-1}) according to the models ensemble. Each map represents the change of annual minimums for future scenarios (minimum of the 20-years periods indicating a specific warming level) from a baseline period (minimum of 2006-2015).

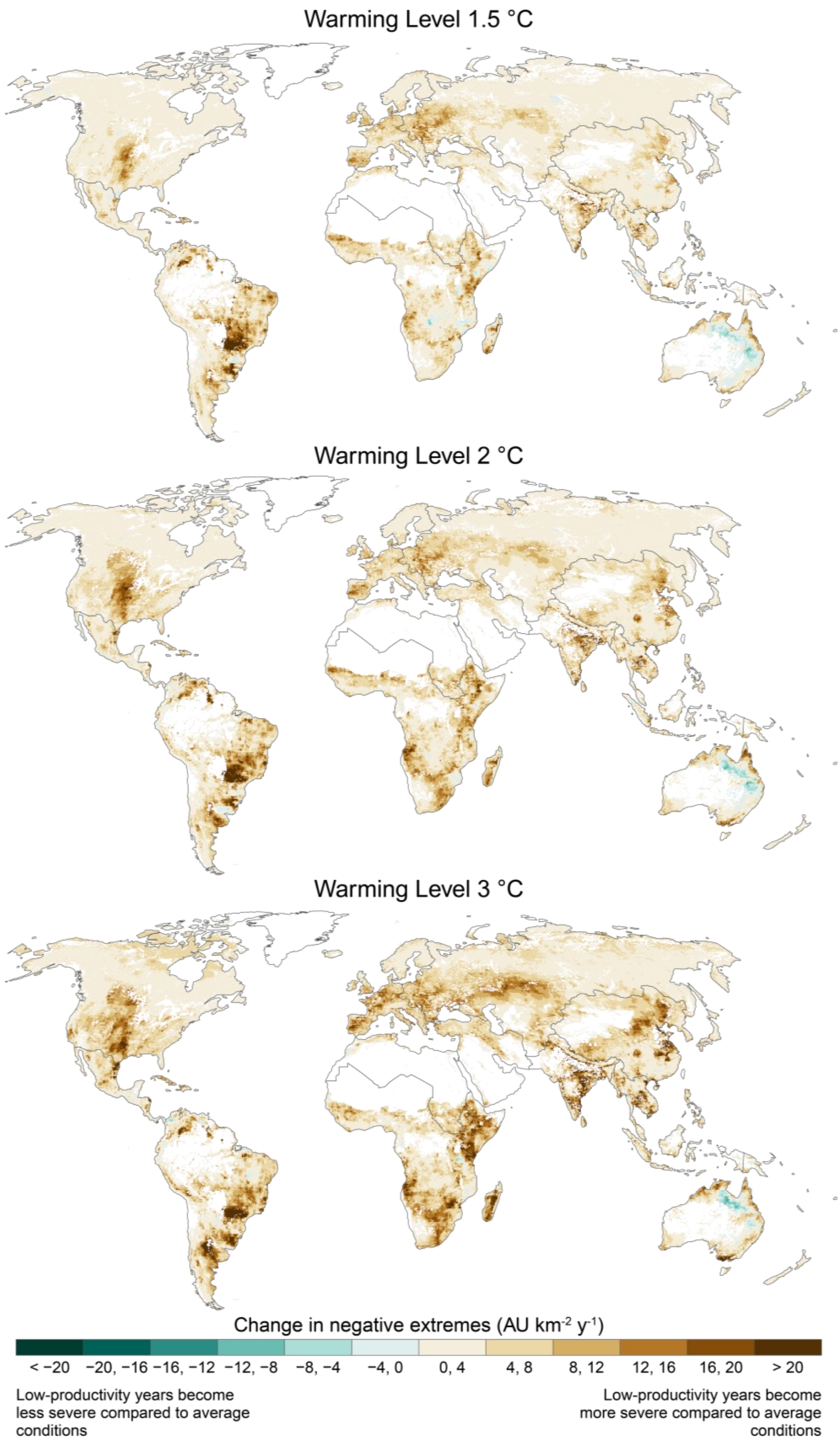

Figure 15. Absolute change (AU km^{-2} y^{-1}) of negative extremes (difference between the average and minimum annual carrying capacity of a specific time period) according to the models ensemble. Each map indicates how much the difference between average and minimum annual carrying capacity of future scenarios will change from the existing differences of the period 2006-2015.

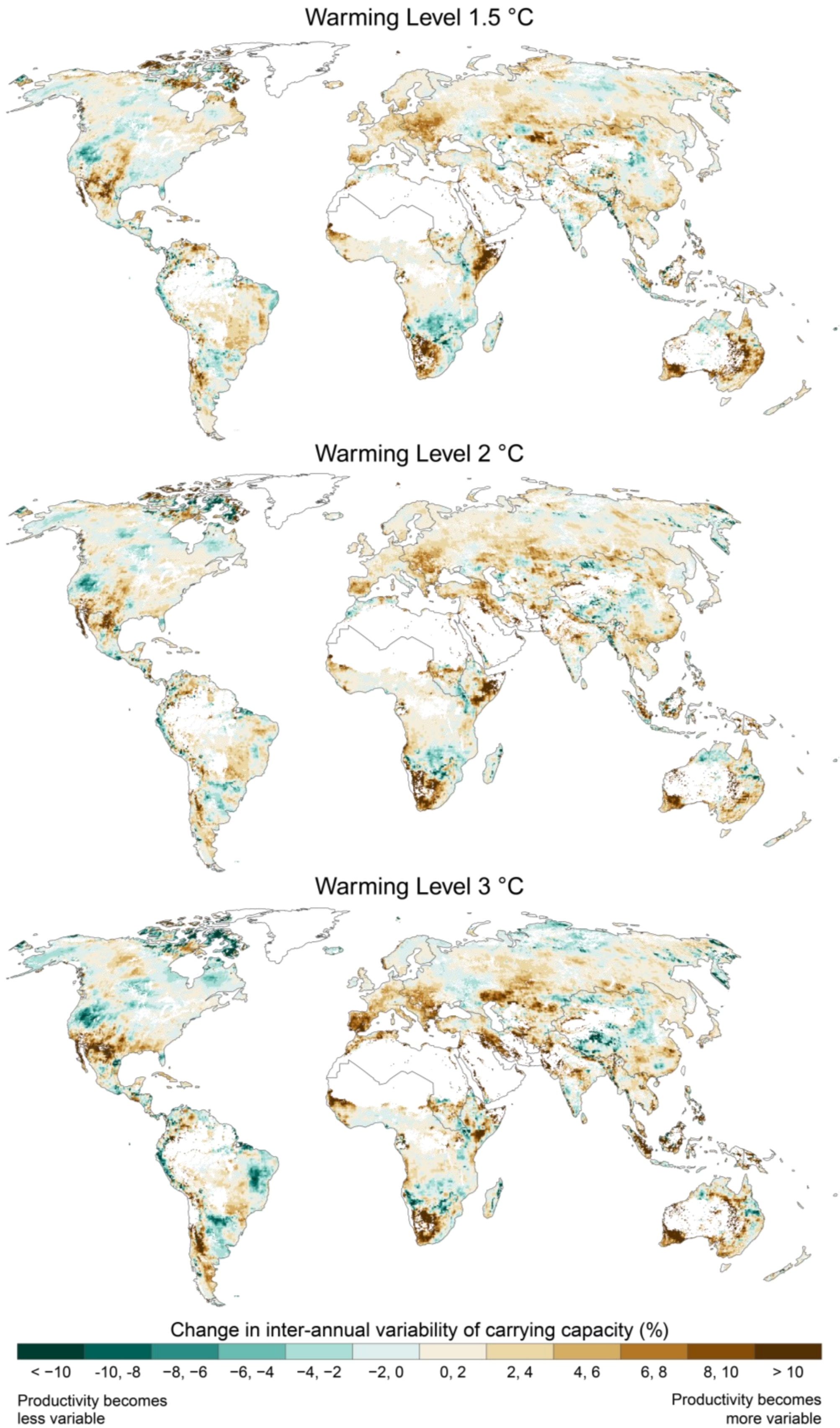

Figure 16. Change of inter-annual variability of annual carrying capacity expressed as coefficient of variation (CV) (%). Each map represents the change for future scenarios expressed as warming levels (20-years periods) from a baseline period (2006-2015).

4.2. Identification of hotspots

As seen in Table 8, the estimations of AGB and CC have different orders of magnitude depending on the VM adopted (*Appendix - Figure 28*). Therefore, the analysis of the results only as a models ensemble could create some inconsistencies. Indeed, the presence of outliers could influence significantly the average values presented in Section 4.2, thus not allowing complete identification of negative hotspots.

Therefore, it was decided to identify hotspots by models agreement, as a higher number of models agreeing on a specific trend could be associated with a high probability that this trend might occur in the future. In this way, we could identify the areas for which most of the models predict a negative trend, independently of its order of magnitude.

Figure 17 allows identification of areas where climate change might have negative impacts on grasslands CC. Red areas represent those where the majority of the models predict decreasing CC, thus identifying the grasslands that will be the most vulnerable to climate change effects. As already highlighted in Section 4.1, these hotspots are mainly located in Australia, Central America, the northern part of South America, part of Brazil, Western Sahel, and the Horn of Africa. However, they represent just a small fraction of the world's grasslands as shown in Table 9.

Table 9. Percentage of the world's grasslands belonging to the classes of Figure 17. These percentages are calculated by combining the rasters of Figure 13 with the fraction of grassland in 5 arc/min resolution cells shown in Figure 10. Therefore, they are actually relative to the study area shown in Figure 5.

	Percentage of grasslands where models predict decreasing carrying capacity			
% of models agreeing	< 25 %	25 – 50 %	50 – 75 %	≥ 75 %
Warming level 1.5 °C	76%	16%	6%	2%
Warming level 2 °C	82%	14%	4%	< 1%
Warming level 3 °C	86%	11%	3%	< 1%

It should be noted that these negative hotspots seem to be more widespread under lower WLs. This is due to the combined effect of the higher CO_2 fertilization effect at higher WLs, the climatic averaging operations, and the annual resolution of CC estimations. Further details about these aspects will be discussed in section 5.2. Nevertheless, this apparently higher vulnerability in the next decades should not be neglected. In fact, without any effort to improve the resilience of the most vulnerable areas during this period, it will be hard to benefit from the positive changes predicted in the future.

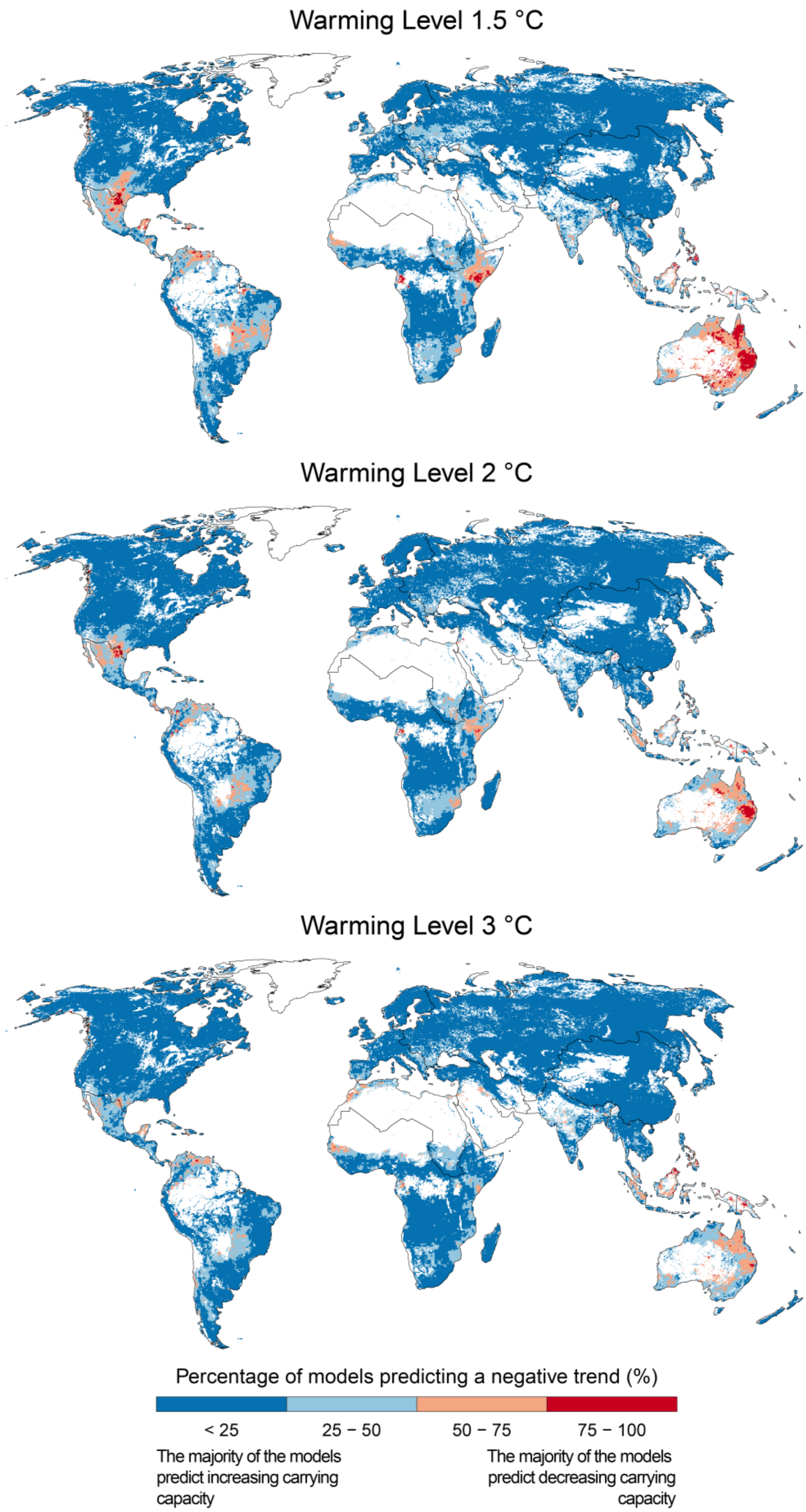

Figure 17. Hotspots identification by model agreement for carrying capacity trends.

Similar temporal patterns can be observed for the hotspots of minimum annual CC, with low-productivity years being projected to become more severe because of climate change. As highlighted in Section 4.1, they are more widespread under lower warming levels, and they are mainly located in the Horn of Africa, Australia, Central America, the Sahel Region, and almost the entirety of South America, where CC is expected to decrease; but also, in Eastern Europe and Southeast Asia, where overall CC is projected to increase.

These negative hotspots are higher in extent compared to the ones of Figure 17. This occurs because the climatic averaging operations mask this increased severity of low-productivity years, as the increases of productivity in non-drought affected years are quite significant. However, because of the distribution of grasslands in these 5 arc/min cells, these negative hotspots still represent a limited fraction of the world's grasslands (Table 10).

Table 10. Percentage of the world's grasslands belonging to the classes of Figure 18.

	Percentage of grasslands where models predict decreasing levels of minimum annual carrying capacity			
% of models agreeing	< 25 %	25 – 50 %	50 – 75 %	≥ 75 %
Warming level 1.5 °C	24%	38%	29%	9%
Warming level 2 °C	39%	32%	23%	6%
Warming level 3 °C	54%	28%	15%	3%

The opposite is true instead if we consider the predicted changes in the inter-annual variability of CC. As shown in Figure 19, in this case the majority of grasslands are expected to experience a more variable productivity (Table 11). The situation seems to be quite steady already under limited warming, with few changes occurring with increasing warming. This might be related to the fact that the severity and frequency of extreme events is projected to be significantly enhanced even under low warming levels (Ipcc, 2022). Because of this, a high number of models agree that productivity will become more unstable in the grasslands of Europe, Brazil, and the majority of China, Sub-Saharan Africa, Central Asia, and Russia. By contrast, increased stability is projected for part of the American grasslands and for the grasslands of Zambia, Zimbabwe, and Mozambique.

Table 11. Percentage of the world's grasslands belonging to the classes of Figure 19.

	Percentage of grasslands where models predict increasing inter-annual variability of carrying capacity			
% of models agreeing	< 25 %	25 – 50 %	50 – 75 %	≥ 75 %
Warming level 1.5 °C	2%	26%	54%	18%
Warming level 2 °C	2%	26%	55%	17%
Warming level 3 °C	4%	30%	51%	15%

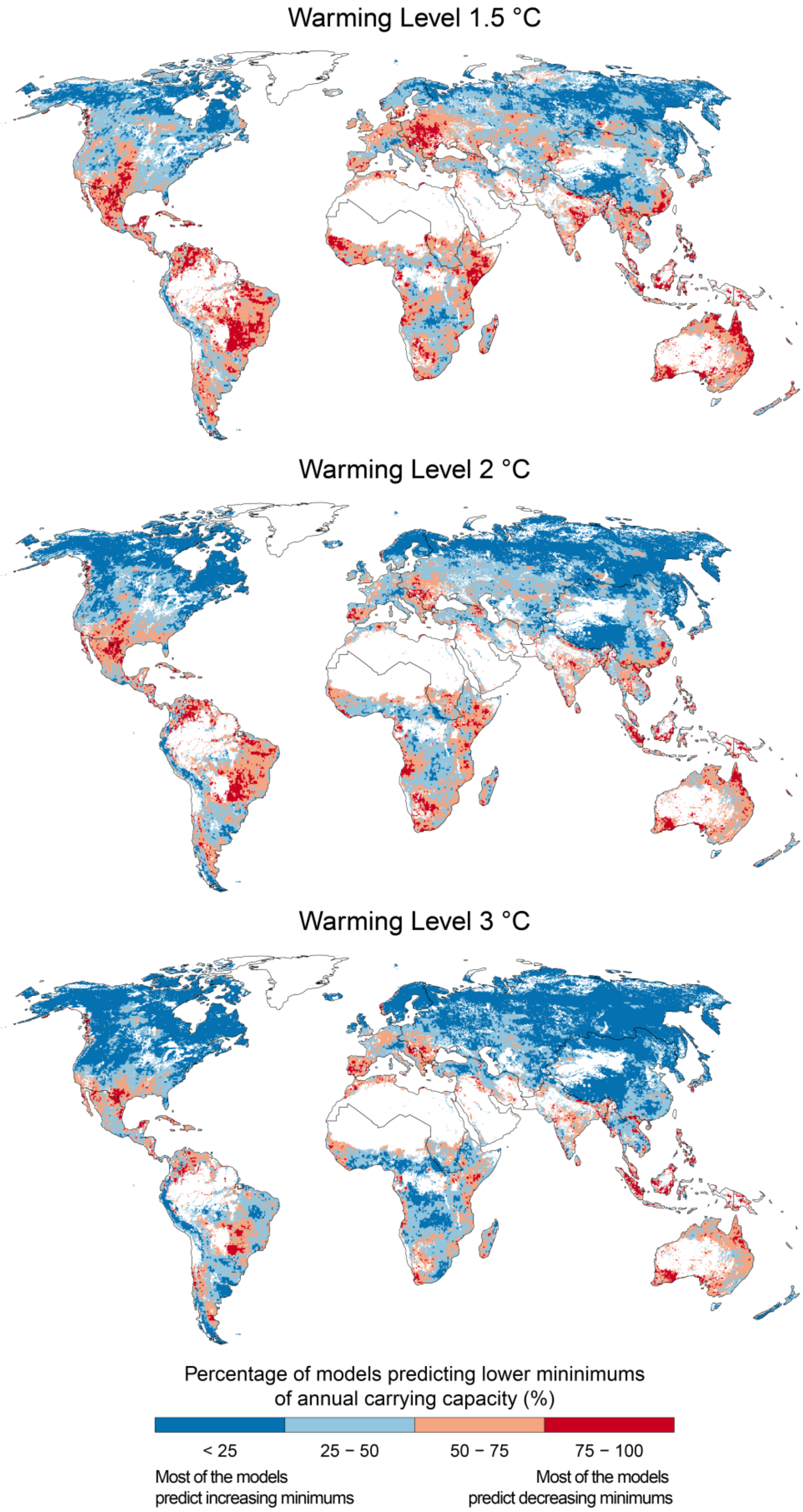

Figure 18. Hotspots identification by model agreement for low-productivity years (minimum annual carrying capacity).

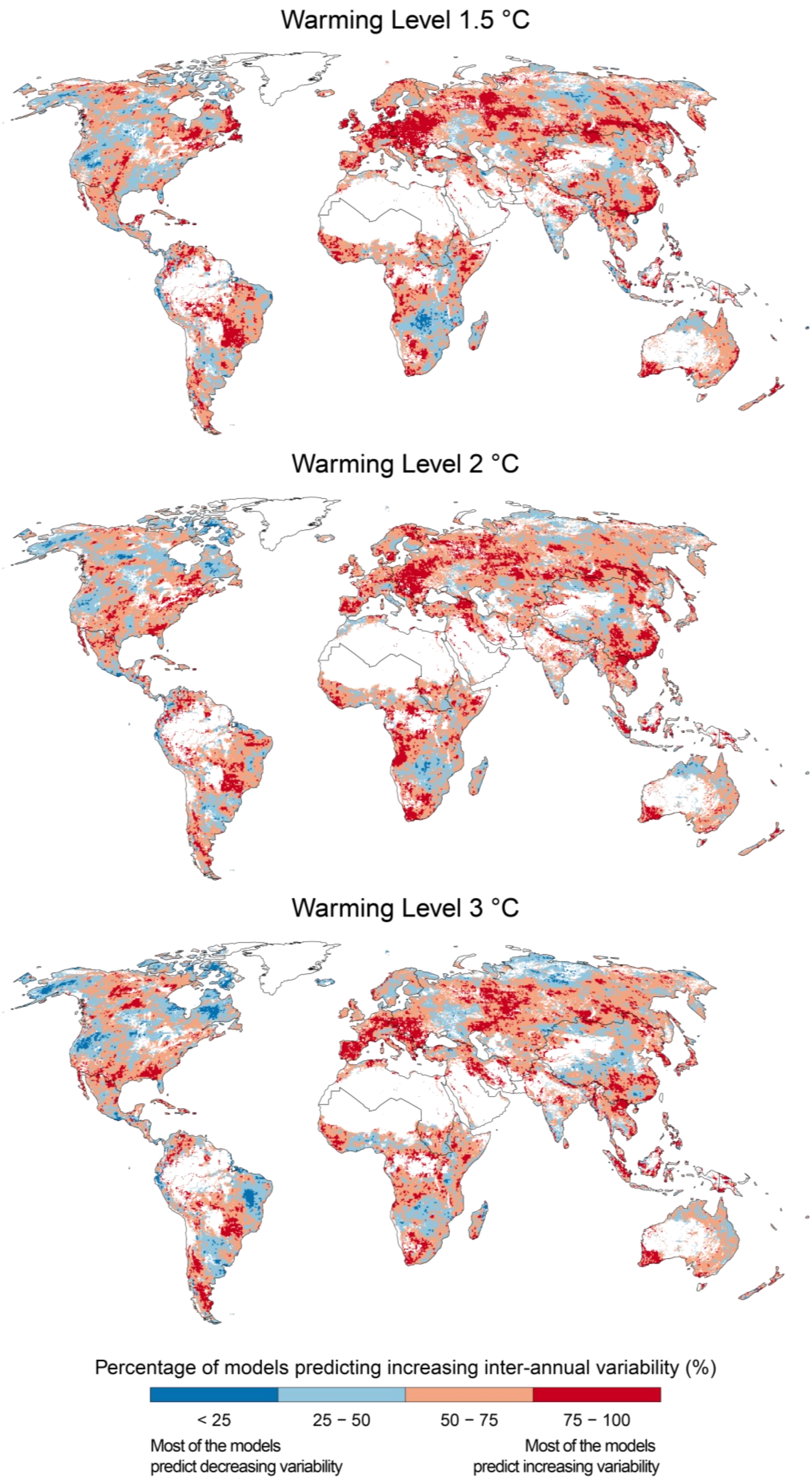

Figure 19. Hotspots identification by model agreement for inter-annual variability.

4.3. Uncertainty assessment

As can be noted in the tables presented in Section 4.2, most of the study area considered in the analysis belongs to the classes that show a higher disagreement between the models combinations. In addition, despite providing a simplified assessment of the uncertainty of CC trends, the analysis of models agreement allows only an understanding of the validity of the direction of the predicted trend, but does not allow evaluation of the differences in its order of magnitude. Therefore, a more detailed analysis is needed to understand the uncertainty of the results presented in Section 4.1 and to evaluate their robustness.

The uncertainty of CC projections was assessed by calculating the CV of the absolute changes of CC determined by all the models combination for each specific WL, and is presented in Figure 20. As it can be observed, the CV of the models results is very high, indicating a high dispersion of the 20 different projections from their mean, and thus implying a high uncertainty of the results presented in Figure 13. The highest uncertainty is observed for the grasslands of Central America, Northern South America, Brazil, Southern and Eastern Africa, the Sahel Region, especially Sudan, and parts of Australia, areas where the agreement of the models on the direction of the future trend was already limited, as shown in Figure 17. The uncertainty is instead lowest for the grasslands where most of the models agreed on a future decrease of CC.

This high uncertainty of future projections is the result of the combined effect of differences in the modelling of VMs and in the climate inputs provided by the GCMs. First of all, the specific VM adopted is what defines the order of magnitude of NPP, and consequently AGB and CC estimations. Generally, the lowest values of CC are produced by CLM4.5, while the maximum ones are estimated by LPJ-GUESS and VISIT (Table 8, *Appendix - Figure 28*). This in part explains the high uncertainty shown in Figure 20, as the order of magnitude of the absolute trends of CC (AU km^{-2} y^{-1}) is directly dependent on the VM adopted. But this is not the only reason, as this uncertainty is very similar even when calculated for the relative trends. Indeed, the VMs influence future projections also through their response to changing climatic patterns, which is determined by the modeling features highlighted in Table 3. In particular, differences in the modelling of drought mortality, nutrients cycling, and vegetations dynamics are responsible for the notable differences in future CC projections. Indeed, VMs that do not describe vegetation as dynamic (CLM4.5, VISIT) usually estimate more limited increases of CC. At the same time, VMs models that do not consider nitrogen limitations (LPJmL, ORCHIDEE) are responsible for the highest projected increases of CC (Table 8).

However, despite the great influence that VMs have on the results, the high uncertainty of future projections is also related to the great influence of the GCM that was used as input to produce future NPP estimations. Indeed, the GCM that is used as forcing both defines specific future climatic patterns and determines the rapidity of such changes. In particular, CO_2 levels differ between same WLs because of the different rapidity of temperature change predicted by the GCMs (Figure 4), thus the WLs associated with slower warming pathways (GFDL-ESM2M, MIROC5) are being characterized by higher CO_2 effects.

For this reason, it has been decided to also group the results by GCM used as forcing, thus producing 4 different models ensembles for each WL considered. This procedure allowed the differences between future warming scenarios to be highlighted, distinguishing between the effects of rapid or slower warming.

The benefits of this approach can be seen in Figure 29 (*Appendix*), which shows the predicted relative change in CC (%) according to the ensembles of models grouped by forcing GCM. Here, significant differences between the negative hotspots of each different climate scenario can be noted, both in terms of severity and geographical extent (e.g., Sudan, Western Sahel). In addition, it can be clearly observed how the rapidity of warming will have an impact on future CC. Indeed, under rapid warming scenarios (HadGEM2-ES, IPSL-CM5A-LR), negative hotspots (where CC decreases) are more widespread and severe. By contrast, the highest increases in CC are observed for slower warming pathways (GFDL-ESM2M, MIROC5), as they are characterized by a stronger CO_2 fertilization effect. The same can be said for the severity of low-productivity years (*Appendix - Figure 30*), as slower warming scenarios are associated with higher increases of minimum annual CC, and thus decreasing severity of low-productivity years. In particular, these differences become more evident at higher WLs, where CO_2 concentrations, and thus the strength of fertilization effect, differ the most.

Given the above, further attention should be paid to consideration of multiple climate scenarios when predicting future trends of ecosystems productivity, as already highlighted by Boone et al. (2018) and Tian et al. (2021).

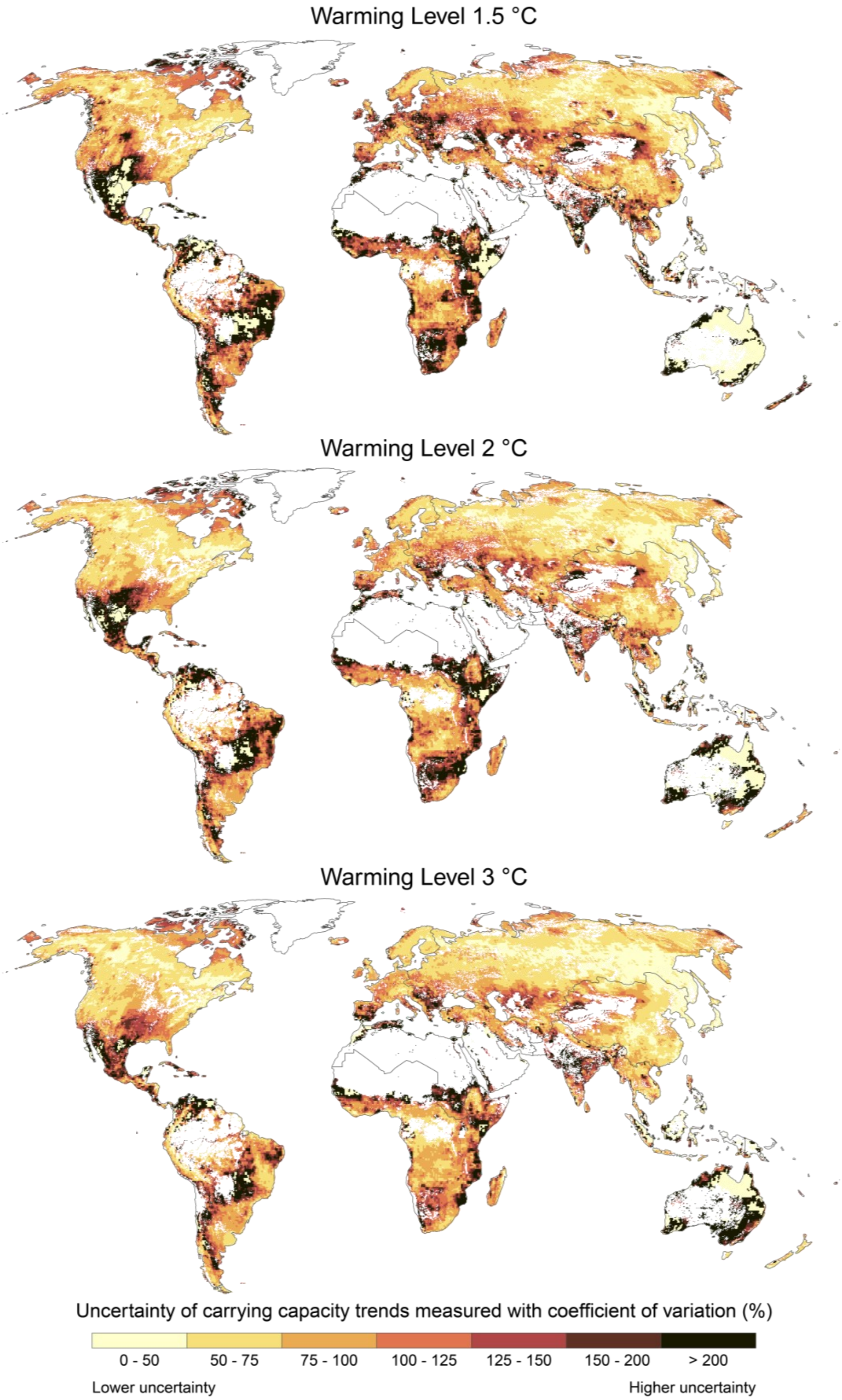

Figure 20. Uncertainty of carrying capacity trends. The uncertainty is expressed as the coefficient of variation of the absolute changes of carrying capacity predicted by the 20 models combination for each specific warming level.

5. Discussion

5.1. Comparison with other studies

The comparison between global grazing studies is always challenging and sometimes it can highlight inconsistencies on a regional level for estimated productivities, potential opportunities, and future projections. Indeed, significant differences between studies can arise from the differences in the methodology adopted to estimate productivity levels, the way in which net primary productivity (NPP) estimations are obtained (e.g., satellite-based estimations or models projections), and on the study area that is considered (Fetzel et al., 2017).

In addition to these challenges, up to date, the research on future grasslands productivity has been narrow and it presents multiple limitations. First of all, most of the studies focus on the effects of climate change on ecosystems productivity only at global level (Gao et al., 2022; Kolby Smith et al., 2016; Li et al., 2015; Tian et al., 2021), generally providing aggregate results (values, figures, and discussion) that do not distinguish between different areas and ecosystems of the world, and that enable only a limited comparability. The few studies that specifically focus on future grasslands productivity have instead a more limited spatial extent, ranging from regional studies (Gao et al., 2016a; Hufkens et al., 2016; Zarei et al., 2021) to more global ones (Godde et al., 2020), but still limited to rangelands only (i.e., only areas of vegetation suitable for direct grazing and browsing by herbivores). In addition to this, future projections of productivity are usually limited to NPP levels, with the exception of Godde et al. (2020), and most importantly they lack intercomparison between different vegetation models (VMs) (Boone et al., 2018; Godde et al., 2020; Tian et al., 2021).

Despite the challenges highlighted above, the results presented in Section 4 agree well with current research and are highly supported by the specific literature on the topic.

In general, historical climate change has been proven to have been beneficial for global NPP, especially in the Northern Hemisphere, increasing in the last decades according to both satellite data and models estimations (Gao et al., 2022; Kolby Smith et al., 2016; Li et al., 2015). This trend has been favoured by increasing temperatures and CO_2 levels, which have been shown to be generally correlated to higher productivities, and is projected to continue in the future (Gang et al., 2017; Tian et al., 2021), with discussions limited to the rate of this increase.

According to Tian et al. (2021), under the RCP 8.5 scenario, the global NPP is projected to increase by 15% and 27% for a warming of 1.5 °C and 2 °C respectively. These trends have been produced through the use of NASA ModelE2-YIBs and 19 CMIP5 scenarios and show similar geographical patterns to those shown in Figure 31 (*Appendix*), with NPP increasing globally, except for parts of Eastern South America and Western Sahel. Despite this agreement, the rate of the projected NPP increase is higher than what is predicted by the models considered in this analysis, which on average estimate NPP to increase by 7.1% and 12.6% for a warming of 1.5 °C and 2 °C respectively (Table 12. Change of net primary productivity (NPP) of global grasslands according to each model combination. *Appendix*). This inconsistency stems from Tian et al.'s inclusion of forest ecosystems, which are expected to experience more substantial NPP increases than grasslands (Pan et al., 2022), and their choice of the 1996-2005 period as a reference, rather than the 2006-2015 period used in this study.

Similar results were obtained by Gang et al. (2017), who through the use of a mathematical model predicted an increase in future global NPP, especially for the RCP 8.5 scenario. In particular, despite a reduction of their extent (an aspect not considered in this analysis), globally grasslands showed an increasing NPP, even without considering the effects of CO_2 fertilization. Because of these assumptions and the differences in the methodology adopted, further comparisons were not possible.

More specific results were instead obtained by Havlík et al. (2015) who through the use of EPIC and LPJmL models predicted increasing grass yields for different regions of the world. In particular, they argue that even though climate change sometimes affected crop yields negatively, it could be beneficial for grasslands productivity, showing opportunities for the intensification of grazing systems. According to their results and in line with what has been presented in Figure 11, higher relative increases are projected for North America and East Asia, while a more moderate increase is projected for Latin America. High uncertainty is instead observed for Oceania, Sub-Saharan Africa, and Southeast Asia.

In addition, multiple regional studies agree on the results presented in Section 4. In particular, Gao et al. (2016a) and Zarei et al. (2021) predicted respectively increasing NPP for the Qinghai-Tibetan Plateau and the grasslands of Tanzania under the RCP 8.5 scenario. More specifically, Gao et al. (2016a), with the use of a modified version of LPJ model, predicted that by 2070 the NPP of the Qinghai-Tibetan Plateau will increase by 134% from

1970 levels. This mirrors what is presented in Figure 31, where almost all the Qinghai-Tibetan Plateau shows an NPP increase higher than 100% for a warming of 3 °C, which roughly occurs around 2070.

Similarly, Hufkens et al. (2016) predicted that, despite the increasing aridity, the productivity of North American grasslands will increase for the same scenario, even without considering the effects of CO_2 fertilization. This is also shown in Figure 31 (*Appendix*), but the differences in the methodology adopted limit the comparability between the studies.

Nevertheless, despite agreeing with multiple global and regional studies, the results presented in Section 4 are not fully supported by the findings of Boone et al. (2018) and Godde et al. (2020). In particular, Boone et al. (2018) argued that global NPP may decline by 2050 under the RCP 8.5 scenario, despite a slight increase in herbaceous productivity. This is mainly due to the large productivity decline projected for Sub-Saharan Africa, which is in contrast with what has been shown in Figure 13. Despite this, their results agree on the increasing trends predicted for North America and other temperate northern rangelands, and on the decreases projected for Australia. Similarly, Godde et al. (2020) predicted decreasing herbaceous biomass across global rangelands, with significant reductions in Australia, Sub-Saharan Africa, but also North America. Despite this disagreement, their results are consistent with the predicted increasing inter-annual variability of herbaceous biomass, despite some spatial heterogeneities.

This inconsistency on the future trends of Sub-Saharan grasslands might be the result of the overly optimistic approach adopted in this analysis, from the equation used to allocate the fraction of NPP to aboveground biomass (AGB), to the modelled strength of the CO_2 fertilization effect, that might be better described by the model adopted by Boone et al. (2018) and Godde et al. (2020) (G-Range). Nevertheless, it's crucial to note that, as emphasized by Tian et al. (2021), relying solely on one vegetation model may lack robustness, as different models have demonstrated divergence in their projections in certain instances.

5.2. Interpretation of the results

The response of grassland ecosystems to climate change is still unclear and highly debated. This is because the mechanisms that affect grasslands productivity are complex, strongly interlinked, highly dependent on the type of grasses, and site-specific (Quan et al., 2020).

These two latter aspects are the main reasons for the notable differences in current available studies (Puche et al., 2023; Wu et al., 2021) and is what prevents the generalization of the identified patterns on a global scale. Despite this, there is growing consensus on the fact that increasing temperatures and CO_2 levels can be beneficial for plants productivity (Puche et al., 2023; Reyes-Fox et al., 2014; Sun et al., 2021b), and thus the results presented in Section 4 have a strong physical explanation.

5.2.1. Warming effects on grasslands productivity

Increasing temperatures have been shown generally to be positively correlated with NPP, and thus AGB, when not coupled with nutrients and water limitations. According to Sun et al. (2021) this is explained by the fact that higher temperatures prolong the growing season, thus stimulating annual plant productivity, and are associated with increased microbial activity, leading to higher mineralization and nitrification rates, and thus increasing nutrient availability. In addition to this, multiple studies have shown that even though both plant photosynthesis and respiration are enhanced by warming, their difference increases under a hotter climate, thus leading to higher carbon (C) accumulation rates (Liang et al., 2013; Puche et al., 2023; Tian et al., 2021).

The benefits of increasing warming are higher where plant growth is constrained by low temperatures (Gang et al., 2017; Tian et al., 2021). Here, in general, increasing temperatures have the combined effect of stimulating photosynthetic activity and lengthening the growing season, thus leading to a highly increased annual productivity. This in part explains the high relative increase in carrying capacity (CC) predicted by the models in the Northern Hemisphere, especially in the grasslands of Russia and Canada, China, and Central Asia (*Appendix - Figure 24*). This trend has already been observed in Kyrgyzstan, Tajikistan, and the Tibetan Plateau, where the analysis of historical data has shown increased productivity (Umuhoza et al., 2021; Zhang et al., 2018), and is projected to continue under future warming (Gao et al., 2016a).

The benefits of increasing warming are instead more limited where temperatures are already favorable to plant growth (low latitudes). Here, as shown by Tian et al. (2021), even though warming is stronger, plant respiration increases significantly, partially dampening the projected enhancements in GPP and thus leading to moderate relative changes in NPP. This explains why the predicted relative increases of AGB and CC are more limited in South

America and Sub-Saharan Africa (Figure 11), where the tropical climate is already able to support very high productivity levels.

However, despite these generally positive effects, prolonged periods of high temperatures coupled with limited precipitation could eventually exacerbate water stress, thus leading to a reduction of NPP, as it is predicted in some cases for Australia and Central America. In this case, the response of grasslands is still debated, and it is highly dependent on the effects of CO_2 fertilization.

5.2.2. Effects of increasing CO_2 levels on grasslands productivity

Increasing CO_2 levels are beneficial to plant growth and they are the main driver of the expected increase in global NPP (Kolby Smith et al., 2016; Tian et al., 2021; Wieder et al., 2015). Indeed, as shown by multiple studies, without the CO_2 fertilization effect the future changes in global climate would instead lead only to moderate NPP increases in the subtropics and huge decreases in tropical regions (Boone et al., 2018; Puche et al., 2023; Tian et al., 2021).

Higher CO_2 concentrations have been shown to enhance photosynthesis rates more than respiration ones, thus increasing photosynthetic carbon gain and biomass production (Puche et al., 2023). In addition to this, Reyes-Fox et al. (2014) showed that increasing CO_2 levels are also responsible for the lengthening of the growing season, thus favouring higher annual productivity gains. Increasing CO_2 levels are also expected to improve plants' water use by reducing stomatal conductance and consequently dampening water losses through transpiration (Puche et al., 2023). This latter aspect explains why increasing temperatures can have an overall positive contribution on the productivity of hot grasslands, as it allows plants to minimize the effects of short-term droughts (Puche et al., 2023; Roy et al., 2016).

Higher warming levels (WLs) are associated to higher CO_2 concentrations and thus with a higher CO_2 fertilization effect. The same can be said for slower warming pathways, which indeed predict higher CO_2 concentrations for each WL analysed. This explains why the highest increases in CC are projected to occur under a warming of 3 °C (Figure 13) and why, for the same WL, they are more significant for the climate scenarios that predict a slower warming, namely GFDL-ESM2M and MIROC5 (*Appendix - Figure 29*). The CO_2 fertilization effect is also responsible for the projected increase in minimum annual levels of CC across multiple regions of the world (Figure 14).

Despite this, the strength of this biological mechanism is still debated and it might be overestimated by models (Havlík et al., 2015; Wieder et al., 2015). Further comments about this aspect will be made in Section 5.4.3.

5.2.3. Effects of extreme events on the stability of grasslands productivity

Grassland productivity is sensitive to climate variability, and extreme events, such as heat waves and droughts, can be responsible for high inter-annual (year-to-year) and intra-annual (within a year) variations of available biomass (Godde et al., 2020). As the severity, frequency, and duration of these extreme events are expected to increase under climate change (O'Mara, 2012; Puche et al., 2023), concern is growing that grasslands CC will become more variable in the future. Indeed, as Gao et al. (2022) have shown, the stability of productivity of open, grass- and forb-dominated (OGFD) ecosystems had already decreased between 1982 and 2015, despite the overall increase in vegetation productivity. However, despite these risks, multiple studies have shown that elevated CO_2 concentrations can mitigate the effect of extreme events on grassland productivity, thus increasing their resilience (Puche et al., 2023; Roy et al., 2016). This is because the improvements in water use can mitigate heat-stress, while the increases in root growth and nitrogen uptake during the extreme event are able to boost grasslands recovery after drought.

This increased severity of extreme events and improved resilience under elevated CO_2 levels is what in part explains the trends presented in Figure 14 and Figure 15. In particular, it can be observed that annual minimums of CC decrease in most of the grasslands under a warming of 1.5 °C. This is due to the fact that the severity and frequency of extreme events is expected to be significantly enhanced even under low warming levels (Ipcc, 2022), and by the limited mitigation potential of the CO_2 fertilization at such levels. Only at higher warming is the mitigation potential of elevated CO_2 concentrations effective in counteracting the negative effect of extreme events. The same could be said for slower warming pathways, that show more limited decreases in minimum CC because of the stronger CO_2 fertilization effect (*Appendix* - Figure 30).

Not only can extreme events affect the minimum annual CC, but they also significantly influence the stability of grasslands productivity, as shown by the overall increase in inter-annual variability of CC (Figure 16). In addition, as highlighted in Figure 15, because of the increasing severity, frequency, and duration of extreme events, adaptation to low-productivity years will become more challenging, as their difference from average conditions will increase in almost every region of the world. These increasing challenges could then offset the benefits of increasing productivity in multiple grasslands of the world.

5.2.4. Effects of the temporal resolution of the analysis on the results

As discussed in section 4.1, the analysis of climatic averages is not always able to identify all the impacts that climate change will have on grassland CC, and this is one of the main reasons for such positive results presented in Figure 13. Focusing only on the analysis of climatic averages would provide an incomplete picture of how grasslands will respond to future climatic patterns and CO_2 concentrations. Indeed, in general, the effect of increasing temperatures and CO_2 levels in periods of sufficient water availability is such that annual CC estimations increase significantly from baseline levels. Therefore, averaging operations can hide the decreases of annual productivity during drought-affected years if negative extremes are not as frequent as normal conditions. However, this does not mean that climate change will not generate any risk for grasslands management and livestock grazing.

In general, the areas that show a decreasing trend of average annual CC (Figure 17) can be identified already as the most vulnerable to drought-related risks, both in terms of productivity and of variability. Nevertheless, there might be multiple additional regions of the world where climate change will increase the risks and challenges related to livestock grazing, even if the influence of heat-related productivity declines is not shown by the climatic average. Therefore, it is important to focus also on the effects that climate change will have on low-productivity years.

However, because of the annual resolution of CC estimations, the results presented in section 4 could still be overly positive. Indeed, as shown by Hufkens et al. (2016), on an annual scale, the increases in growing season and productivity during the months unaffected by heat stress can offset the drought-related productivity declines. For this reason, as extreme temperatures usually do not affect productivity over an entire year, the annual predictions of CC can still show an overall increase, even if the severity of drought periods could substantially affect the possibility of taking advantage of this increased productivity. Further comments about the limitations related to this aspect and possible improvements will be explored in sections 5.4.4 and 5.4.5.

5.3. Grasslands, climate change, and food security

Grasslands are an important source of forage for livestock systems and they play an essential role in the food security of most low-income countries (Herrero et al., 2013). In the next decades, the increasing demand for livestock products and population growth will increase the reliance on these ecosystems (Godde et al., 2020), raising concerns about the consequences of such anthropogenic pressures on the health of grassland resources. At the same time, climate change will directly affect the status and the productivity of these ecosystems (O'Mara, 2012), thus generating new opportunities as well as new challenges for grassland management and food security. In particular, understanding how climate change will affect the carrying capacity of grasslands is essential to understand the possible impacts that such increasing anthropogenic pressure might have on the health of these ecosystems and the services that they provide.

The results of this analysis can be used therefore to highlight future threats and opportunities for livestock production and to guide the development of effective policies to preserve grasslands health in spite of the projected increasing demand for livestock products.

However, it should be remembered that considerations on future levels of livestock productivity are complex and should not only be limited to the possible changes of grass productivity and forage availability. In particular, it should be noted that this analysis does not consider human disturbances, such as conversion of grasslands to cropland, or changes in irrigation and other management practices. These aspects will strongly dictate how livestock systems will respond to climate change and how they will affect the future health of grasslands resources.

5.3.1. Climate change effects on forage availability

As deeply discussed in Section 4, this study finds that climate change may positively impact vegetation productivity in most of the world's grasslands, with negative trends limited to a small fraction of global grasslands (Table 9). However, these positive findings cannot be directly related to a future growth of livestock products from grasslands, as climate change will generate at the same time additional challenges that could even prevent from benefitting from this increased productivity. In particular, most of the grasslands will experience increasing year-to-year variability of CC (Table 11) as well as an increasing severity of low-productivity years (Figure 15). If not tackled correctly through efficient adaptation strategies, these challenges will offset the benefits that could be achieved from the predicted increasing productivity. Indeed, prolonged periods of forage shortage are already one of the main challenges for grazing systems (Fetzel et al., 2017), as they mainly rely on directly grazed biomass, and they are particularly severe in areas of limited adaptive capacity (limited availability of additional feeds, effective storage systems, economic resources, mobility, and efficiency of biomass utilization), such as pastoral communities. As highlighted by Herrero et al. (2013), grazing systems produce only a small fraction of livestock products on a global scale, but they are of vital importance for the livelihoods of millions of people, mainly in the developing world. Here, the effects of increasing year-to-year variability of CC and increasing severity of low-productivity years will be the most severe, and might event prevent these communities to benefit from increasing productivities, threatening the livelihoods of millions of people. In particular, as highlighted by Fetzel et al. (2017), these impacts will be more significant for grasslands that are already above their carrying capacity, as the available resources are already overexploited.

Given the above, in order to effectively take advantage of the positive effects that climate change might have on grasslands productivity, and fight at the same time the management challenges that it could generate, multiple adaptation strategies should be developed. In particular, to protect the smallholders in low-income countries from increasing inter-annual variability and severity of low-productivity years, strategies should focus on increasing the availability of additional feeds (feed crops, crop residues, and eventual supplements) and on their integration in ruminants' diets to both improve livestock's conversion efficiency and reduce the dependency from directly grazed biomass. In addition, widespread efficient storage systems should be developed to exploit the excess of available biomass during productive periods to increase the resilience of smallholders to prolonged periods of shortage. At the same time, constraints to the mobility of livestock keepers should be reduced, with mobility being described as a key adaptation strategy in arid and semi-arid systems by Godde et al. (2020).

To conclude, thanks to the predicted increases in productivity, grasslands might be able to sustain part of the growth of the demand for livestock products without being excessively exploited. However, in order for this to be possible, context-specific adaptation strategies should be developed, especially for areas where livestock production and food security are highly dependent on smallholder grazing systems (mainly Sub-Saharan Africa, Latin

America, and South Asia). This will require coordinated investments and the participation of different actors, as well as significant efforts to guarantee the implementation of such strategies by livestock keepers, that might not always be able to change their livestock management practices if not well supported.

5.3.2. Climate change effects on forage quality and livestock

Despite the potential positive effects of climate change on forage availability, considerations on the future productivity levels of livestock products from grasslands are not this straightforward. Indeed, the amount of available forage is just one factor affecting these future trends, and it interacts in a complex way with multiple others, such as the future quality of forage, and the potential effects that climate change could have on livestock health and efficiencies.

Multiple studies have highlighted that elevated CO_2 levels might be responsible for a decline of forage quality because of the increased crude fibre content of grasses at the expense of their crude protein and fat contents (Erda et al., 2005; Seibert et al., 2021). Similarly, forage quality might also be reduced by prolonged periods of heat stress and droughts (Seibert et al., 2021), which are expected to become more common and severe in the future.

At the same time, forage quality could also be affected by changes in herbaceous species composition. In particular, climate change might increase the ratio of C4 to C3 grasses in grasslands, thus decreasing their CC as C4 have usually lower nutritive value for grazing animals (Lin et al., 2013). Furthermore, in some areas bush encroachment might additionally decrease the amount of AGB that could be actually grazed by animals (Tietjen et al., 2009).

In addition to the effects on forage quality, climate change might threaten the productivity of livestock in multiple ways. It is still not completely clear how animals will respond to increasing temperatures, but high temperatures might negatively affect their water and forage requirements, as well as their conversion efficiencies and their growth rates (Cheng et al., 2022). In addition, climate extremes will have a negative effect on livestock health, directly affecting mortality rates, while higher temperatures might enhance the diffusion of parasites and infectious pathogens.

These aspects should be carefully considered when evaluating the effects that climate change could have on the production of livestock products from grassland ecosystems.

5.4. Limitations and future directions

5.4.1. Climate change effect on grasslands' biomass partitioning

As described in Section 3.1., the equation developed by Sun et al. (2021b) was adopted to allocate the fraction of NPP to AGB (Eq. 1). This spatial relationship allows consideration of the effect of the local climate (here expressed through temperature and precipitation) on biomass partitioning, enabling the production of more accurate results than what is normally found in global grazing studies, which instead use a single constant for fANPP (Fetzel et al., 2017; Fetzel et al., 2017; Petz et al., 2014; Wolf et al., 2021). According to this relationship (Eq. 1), fANPP is highest in tropical grasslands and savannas, followed by that in temperate grasslands, and is lowest in very arid or cold grasslands. This is explained by the fact that plants tend to allocate more production belowground in stressful environments (e.g., extremely arid or cold areas), while they allocate more production aboveground in favourable ones (e.g., humid and warm areas with no nutrients limitations) (Sun et al., 2021b).

However, despite the higher accuracy in mirroring the global situation, the validity of this spatial relationship under future climates is arguable, as according to Eq.1 an increase in mean annual temperature (MAT) always corresponds to an increase in fANPP. Hence, with global climate scenarios projecting a worldwide rise in MAT, fANPP might exhibit a growing pattern in all grasslands across the globe, eventually even compensating for a reduction of total NPP.

This assumption might not be completely true. Indeed, as shown by Sun et al. (2021b), different grassland types respond differently to temporal temperature increases. In particular, according to the data they analysed, aboveground NPP (ANPP) was negatively correlated with MAT in arid areas, while it was positively correlated in humid grasslands (Figure 21). Therefore, it might happen that fANPP will decrease in arid grasslands under a hotter climate, as already shown by Gao et al. (2019).

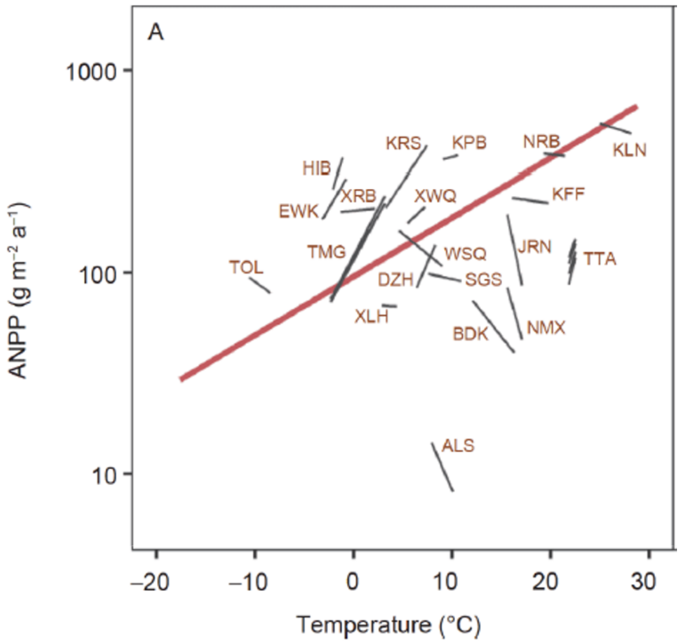

Figure 21. Comparison of spatial models (red lines) and long-term temporal models (black lines) for aboveground net primary productivity (ANPP) and mean annual temperature in global grasslands. Adapted from Sun et al. (2021b).

Because of this potential inconsistency between temporal and spatial patterns, part of the future CC estimations presented in this analysis might be too optimistic. This is the case for part of the grasslands of Mongolia, Kazakhstan, USA, and China, where the predicted increases in CC might not be so marked, and for the grasslands of the Sahel, the Horn of Africa, and part of Australia and Mexico, already fragile ecosystems as highlighted in Section 4.1, where CC might be even lower. This also, in part, explains the differences in the trends of herbaceous biomass in Sub-Saharan Africa noted in the current analysis and from those outlined in the study of Godde et al. (2020).

However, the effects of warming on ANPP are site-specific and depend on multiple factors, thus their generalization on a global scale might be incorrect. In particular, Franco et al. (2020) showed the possibility of observing an increase in biomass allocation aboveground even in water-stressed grasslands because of changes in the below-ground trophic web.

The current status of research regarding this topic is still limited and the response of fANPP to climate change is not quantified yet. By assuming that this relationship (Eq. 1) will still be valid under future climates we are assuming that plants will be able to positively adapt to a different environment, which might not always be the case. Further effort should be put into the development of a temporal relationship for fANPP for different grassland types under projected future climates.

5.4.2. Climate change effect on tree canopy cover and land cover

As discussed in Section 3.2, no variations of the tree canopy cover correction factor were considered throughout the analysis, but this simplified approach could lead to some inaccuracies. Indeed, as highlighted by multiple studies, climate change is expected to have an important effect on plant dynamics, defining new climatic patterns and thus allowing tree species to migrate (Boone et al., 2018; Gang et al., 2017). At the same time, the strength of the CO_2 fertilization effect has been shown to be stronger for woody systems (Pan et al., 2022), meaning that it could affect also the tree canopy cover (and thus the correction factor used in the analysis) of areas where trees are already relatively abundant. Not considering these aspects and maintaining a constant tree cover correction factor could lead to an overestimation of available AGB in areas were temperature and precipitation patterns will favour tree growth and movement.

Despite this, developing a dynamic description of this factor might be very challenging because of the complexity in the relationship between climate change and tree cover and the limited amount of available data, especially when adopting global open access datasets (e.g., ISIMIP).

In addition, as highlighted by Piipponen et al. (2022), the tree cover multiplier function (Figure 7) is still far from perfect and it should be improved

At the same time, the new future temperature and precipitation patterns will not only affect the tree canopy cover but will also be responsible for the expansion or shrinking of current ecosystems. As discussed in Section 3.2, this aspect was not considered here, and the study was conducted for current grasslands resources (specifically for the period 2001-2015). However, as highlighted by Gang et al. (2017), grasslands are expected to shrink under all RCP scenarios because of climate change. In particular, they predicted a significant expansion of temperate forests in the Northern Hemisphere, the establishment of desert vegetation in very hot and arid areas, such as central Australia, and the expansion of savannas in South America. Overall, these dynamics will have a negative effect on the current grassland extent, and thus considerations on the implications of our results for the future production of livestock products from grasslands should take these aspects into account.

5.4.3. Modelled strength of the CO_2 fertilization effect

As highlighted in section 5.2.2, rising atmospheric CO_2 concentrations have been beneficial for global ecosystems productivity and are expected to enhance vegetation growth also in the future. However, as highlighted by Havlík et al. (2015), the strength of the CO_2 fertilization effect is one of the main source of uncertainty in future NPP projections, and multiple studies highlighted that models might overestimate it (Huntingford and Oliver, 2021; Kolby Smith et al., 2016; Wieder et al., 2015).

As shown by Kolby Smith et al. (2016), CMIP5 earth system models (ESM) show higher global-scale CO_2 fertilization effects than satellite-based estimations for the period 1982-2011 (Figure 22). They argue therefore that models might be oversensitive to atmospheric CO_2 concentrations. As supported by other additional studies (Huntingford and Oliver, 2021; Wieder et al., 2015), this might be the result of the oversimplification or complete absence of nutrients cycles in VMs. In particular, as carbon assimilation and plant growth are constrained by nitrogen (N) and phosphorus (P) availability, the amounts of N and P required for the NPP increases simulated by VMs greatly exceed their estimated supply rates. Therefore, when accounting for nutrients inputs constraints, CMIP5 projections of NPP for 2100 are reduced by 19% and 25%, when considering only N limitations or both N and P limitations respectively (Kolby Smith et al., 2016), as shown in Figure 23.

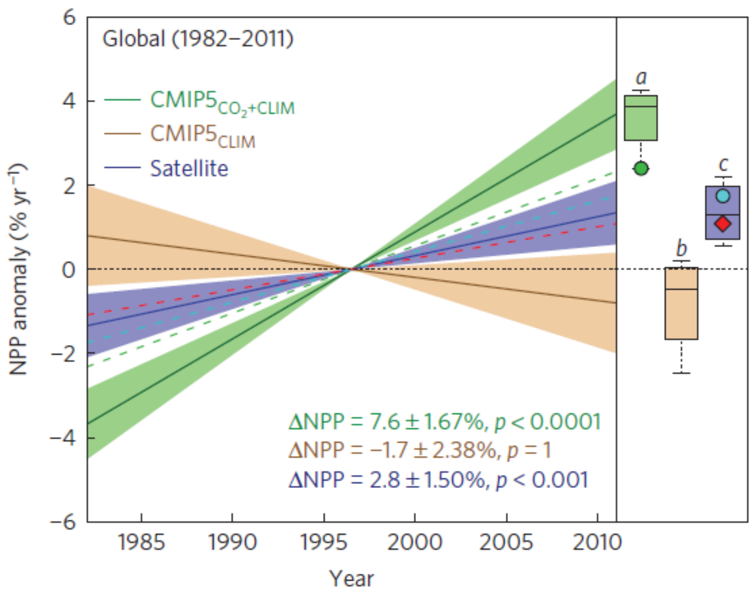

Figure 22. Net primary productivity (NPP) anomaly from 1982 to 2011. The green area indicates global NPP projections produced by CMIP5 models when considering both the effects of historical climate change and CO_2 fertilization effect, while the blue area indicates satellite-based NPP estimations along with their uncertainty. Box and whisker plots (right panels), show the distribution of estimates for the full time period. Source: Kolby Smith et al. (2016).

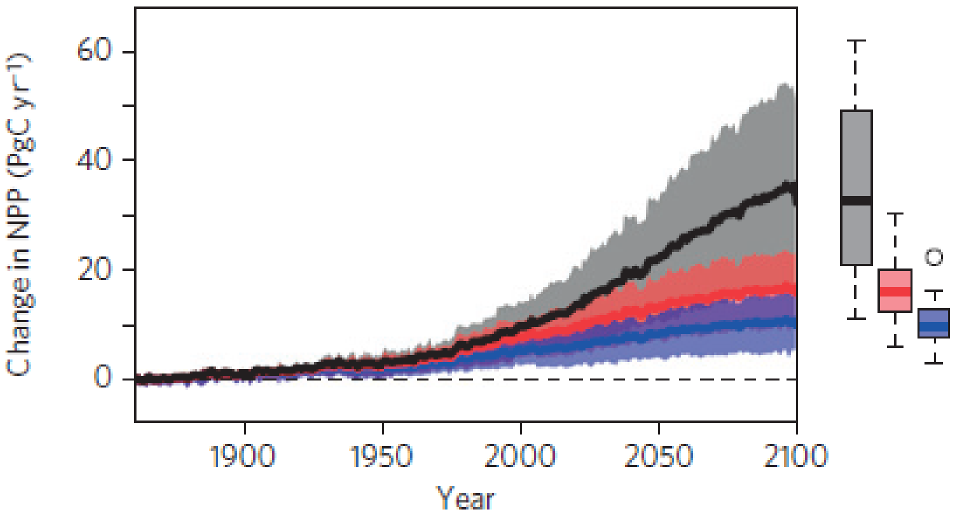

Figure 23. Change in global net primary productivity (NPP) from CMIP5 model projections for RCP 8.5. Original CMIP5 ensemble mean (black), assuming nitrogen limitations (red), assuming nitrogen and phosphorous constraints (blue). Source: Wieder et al. (2015).

Currently, an increasing number of VMs is incorporating N cycle, while the representation of P cycle is still very uncommon (Huntingford and Oliver, 2021). In particular, in the current analysis only three out of the five VMs considered N limitations, with the unconstrained ones (LPJmL and ORCHIDEE) predicting higher NPP increase rates (Table 8). The results presented might therefore provide an overly optimistic estimation of grasslands productivity under a changing climate.

5.4.4. Spatial and temporal resolution

The spatial scale of the analysis (global) is such that it required a relatively coarse resolution (5 arc/min), and some of the datasets had to be aggregated from their original one (land cover map and correction factors rasters). In addition, because of the very high computational expenses of running multiple VMs, the resolution of ISIMIP2b datasets was even lower and equal to 30 arc/min (Frieler et al., 2017).

This aspect should be taken into account when evaluating the uncertainty of the results. In particular, this latter resolution (30 arc/min), is not optimal to describe in detail the vegetation dynamics of a specific area, and the modelled change in NPP might not be even directly related to grasslands unless they cover a large majority of the cell (Havlík et al., 2015). Indeed, as highlighted by Pan et al. (2022), woody systems show greater CO_2 enhancement than grasses, and thus the predicted increase in NPP might be overestimated in cells with just a limited fraction of grassland.

Up to date, global studies on climate change effects on grasslands productivity are still very limited, and the ones that have considered modelled NPP values have adopted a 30 arc/min resolution (Boone et al., 2018; Gao et al., 2016; Gao et al., 2022; Godde et al., 2020). A higher resolution has been achieved only by some regional studies (Hufkens et al., 2016; Zarei et al., 2021; Zhang et al., 2018), which however did not adopt a VM to estimate future NPP or biomass productivity, except for that of Hufkens et al. (2016).

A higher spatial resolution has the evident benefit of enabling a more detailed description of vegetation dynamics, providing more accurate estimations of its response to climate change, but at the same time it limits the study area or the number of different simulations because of the high computational costs. This latter aspect should not be neglected, as the validity of studies using a single VM and a limited number of GCMs might be arguable (Boone et al., 2018; Tian et al., 2021), especially since this study highlighted the important influence that GCMs have on future NPP projections. Therefore, even though the resolution of the current analysis is coarse, it is necessary to accept its limitations and understand the possible drawbacks of using a different one.

The temporal resolution of the analysis is also another limiting element. Indeed, the results presented in the previous sections represent average annual conditions but the monthly variations of CC should be also carefully considered, especially when defining proper stocking rates (Piipponen et al., 2022). As highlighted by multiple studies, the seasonal and monthly variations of available biomass represent an important challenge for grazing, as they define periods of biomass shortage or surplus (Fetzel et al., 2017; Godde et al., 2020). In particular, the productivity gains caused by climate change could be partially or totally offset if they were to occur together with an increase in intra-annual variability (month-to-month) of CC, especially in areas where alternative feeds or storage systems are hardly available. However, with the actual temporal resolution of the analysis these risks might not be identified, as discussed in section 5.2.4. An improved methodology should be developed to take into account the importance of such changes.

5.4.5. Potential improvements

This study is the first of its kind to consider the effect of climate change on global grassland ecosystems according to the predictions of multiple VMs. Despite this, its limitations are still considerable, and multiple improvements could be made to obtain more accurate results.

First, as suggested in Section 5.4.1, a new relationship for biomass partitioning under future climates should be developed in order to better describe the response of different grassland ecosystems to temperature changes. However, because of the complexity of such an approach and the high uncertainty related to it, a different solution would be to consider as input datasets not the models projections of NPP but of carbon mass in AGB, as was done by Godde et al. (2020). However, this is not always possible when using open access datasets, as it is the case with ISIMIP2b simulations, where this information could not be retrieved.

Then, as highlighted in Section 5.4.2, a new dynamic description of the tree cover correction factor should be adopted. In particular, a new relationship should be developed that could take into account the enhanced effect of CO_2 fertilization of woody systems in respect to grasslands. In this way the changes in future NPP could be directly related to grasslands even for cells where trees are relatively abundant, thus reducing the overestimation of NPP increases. Alternatively, instead of considering the total NPP as input datasets, the NPP related to the specific PFTs that for each models define grasslands vegetation could be used. This approach has multiple limitations, however. Indeed, these datasets are not always available (as is the case for multiple ISIMIP2b simulations), and PFTs differ significantly from VMs, thus potentially leading to possible inconsistencies. In addition, as noted by Fetzel et al. (2017), considering only NPP estimations for grassy PFTs could lead to a significant underestimation of potential grazing biomass in shrub-dominated regions, where shrubs can constitute up to 40–50% of the total feed demand.

For more accurate predictions of future production levels of livestock products from grassland resources instead, changes in the spatial dynamics of ecosystems should be taken into account by considering also dynamic land cover maps. However, this information could hardly be retrieved from VMs simulations and might only be able to be obtained from external sources. This could lead to inconsistencies between different VMs, as each of them will predict specific spatial patterns of grassland ecosystems.

More importantly, simulations of future ecosystems productivity should be done by considering nutrients limitations (nitrogen at least) to avoid the overestimation of the CO_2 fertilization effect. When not possible, as in the case of the adoption of open-access simulation results, careful considerations of the VMs adopted should be done, eventually excluding the results of VMs that do not consider nitrogen limitations. However, this approach might reduce significantly the number of available projections, thus limiting the validity of the study as well.

Another important improvement could be achieved by running VMs under an increasing number of different GCMs input climatic data. Despite the significant importance that GCMs have on future NPP trends, we acknowledge that this approach might require too much time and very high computational costs.

To reduce instead the limitations related to the temporal resolution of the analysis, one solution could be to introduce improvements in the methodology for CC estimations. For example, seasonality constraints for biomass availability could be considered in a similar way to that done by Fetzel et al. (2017). In this way, the effect of extreme events on annual CC could be better described, thus leading to less optimistic results. At the same time, there should be consideration of the intra-annual variability of biomass productivity, if such data are available.

Lastly, this analysis should be reproduced for different climate scenarios, in order to understand if path dependency exists. Indeed, despite being a commonly adopted approach in the literature, the consideration only of the results for the RCP 8.5 scenario might neglect eventual differences in the response of terrestrial ecosystems to slower increases of temperature and CO_2 concentrations.

6. Conclusions

In this analysis, future projections of grasslands productivity from five distinct vegetation models (VMs) were combined to obtain a robust estimation of the effects of climate change on grasslands carrying capacity (CC). The results indicate that rising temperatures and CO_2 levels are expected to have a generally positive effect on CC. This means that vegetation productivity in most grasslands around the world will increase, with negative effects primarily concentrated in specific regions such as Australia and the Horn of Africa, affecting only a limited fraction of the world's grasslands.

However, despite the overall positive outlook, there are challenges to consider. Most grasslands will also experience greater year-to-year variability and an increase in the severity of low-productivity years. If these challenges will not be effectively addressed through appropriate adaptation strategies, they could offset the benefits derived from increased productivity. Special attention should be given to smallholders grazing systems in low-income countries, which will be the most vulnerable to such effects.

It is worth noting that in some cases, the predicted trends may be slightly overly optimistic due to the inherent limitations of the models' projections and the methodology employed. Nonetheless, these projections serve as important indicators of future threats and opportunities for livestock production. Therefore, they can be valuable tools for developing effective policies aimed at preserving the health of grasslands, particularly in light of the growing demand for livestock products.

7. References

Amatulli, G., McInerney, D., Sethi, T., Strobl, P., Domisch, S., 2020. Geomorpho90m, empirical evaluation and accuracy assessment of global high-resolution geomorphometric layers. Sci. Data 7, 162. https://doi.org/10.1038/s41597-020-0479-6

Bengtsson, J., Bullock, J.M., Egoh, B., Everson, C., Everson, T., O'Connor, T., O'Farrell, P.J., Smith, H.G., Lindborg, R., 2019. Grasslands-more important for ecosystem services than you might think. Ecosphere 10, e02582. https://doi.org/10.1002/ecs2.2582

Boone, R.B., Conant, R.T., Sircely, J., Thornton, P.K., Herrero, M., 2018. Climate change impacts on selected global rangeland ecosystem services. Glob. Change Biol. 24, 1382–1393. https://doi.org/10.1111/gcb.13995

Boval, M., Dixon, R.M., 2012. The importance of grasslands for animal production and other functions: a review on management and methodological progress in the tropics. Animal 6, 748–762. https://doi.org/10.1017/S1751731112000304

Cheng, M., McCarl, B., Fei, C., 2022. Climate Change and Livestock Production: A Literature Review. Atmosphere 13, 140. https://doi.org/10.3390/atmos13010140

de Leeuw, J., Rizayeva, A., Namazov, E., Bayramov, E., Marshall, M.T., Etzold, J., Neudert, R., 2019. Application of the MODIS MOD 17 Net Primary Production product in grassland carrying capacity assessment. Int. J. Appl. Earth Obs. Geoinformation 78, 66–76. https://doi.org/10.1016/j.jag.2018.09.014

Erda, L., Wei, X., Hui, J., Yinlong, X., Yue, L., Liping, B., Liyong, X., 2005. Climate change impacts on crop yield and quality with CO_2 fertilization in China. Philos. Trans. R. Soc. B Biol. Sci. 360, 2149–2154. https://doi.org/10.1098/rstb.2005.1743

Fetzel, T., Havlik, P., Herrero, M., Erb, K., 2017. Seasonality constraints to livestock grazing intensity. Glob. Change Biol. 23, 1636–1647. https://doi.org/10.1111/gcb.13591

Fetzel, T., Havlik, P., Herrero, M., Kaplan, J.O., Kastner, T., Kroisleitner, C., Rolinski, S., Searchinger, T., Van Bodegom, P.M., Wirsenius, S., Erb, K.-H., 2017. Quantification of uncertainties in global grazing systems assessment: Uncertainties in Global Grazing Data. Glob. Biogeochem. Cycles 31, 1089–1102. https://doi.org/10.1002/2016GB005601

Franco, A.L.C., Gherardi, L.A., De Tomasel, C.M., Andriuzzi, W.S., Ankrom, K.E., Bach, E.M., Guan, P., Sala, O.E., Wall, D.H., 2020. Root herbivory controls the effects of water availability on the partitioning between above- and below-ground grass biomass. Funct. Ecol. 34, 2403–2410. https://doi.org/10.1111/1365-2435.13661

Friedl, M., Sulla-Menashe, D., 2022. MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V061. https://doi.org/10.5067/MODIS/MCD12Q1.061

Frieler, K., Lange, S., Piontek, F., Reyer, C.P.O., Schewe, J., Warszawski, L., Zhao, F., Chini, L., Denvil, S., Emanuel, K., Geiger, T., Halladay, K., Hurtt, G., Mengel, M., Murakami, D., Ostberg, S., Popp, A., Riva, R., Stevanovic, M., Suzuki, T., Volkholz, J., Burke, E., Ciais, P., Ebi, K., Eddy, T.D., Elliott, J., Galbraith, E., Gosling, S.N., Hattermann, F., Hickler, T., Hinkel, J., Hof, C., Huber, V., Jägermeyr, J., Krysanova, V., Marcé, R., Müller Schmied, H., Mouratiadou, I., Pierson, D., Tittensor, D.P., Vautard, R., van Vliet, M., Biber, M.F., Betts, R.A., Bodirsky, B.L., Deryng, D., Frolking, S., Jones, C.D., Lotze, H.K., Lotze-Campen, H., Sahajpal, R., Thonicke, K., Tian, H., Yamagata, Y., 2017. Assessing the impacts of 1.5 °C global warming – simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b). Geosci. Model Dev. 10, 4321–4345. https://doi.org/10.5194/gmd-10-4321-2017

Gang, C., Zhang, Y., Wang, Z., Chen, Y., Yang, Y., Li, J., Cheng, J., Qi, J., Odeh, I., 2017. Modeling the dynamics of distribution, extent, and NPP of global terrestrial ecosystems in response to future climate change. Glob. Planet. Change 148, 153–165. https://doi.org/10.1016/j.gloplacha.2016.12.007

Gao, J., Zhang, L., Tang, Z., Wu, S., 2019. A synthesis of ecosystem aboveground productivity and its process variables under simulated drought stress. J. Ecol. 107, 2519–2531. https://doi.org/10.1111/1365-2745.13218

Gao, Q., Ganjurjav, H., Hu, G., Xu, H., Schwartz, M.W., Gornish, E.S., Zhu, W., 2022. Warming diminishes the stability of primary productivity in global grass- and forb-dominated ecosystems. Environ. Res. Commun. 4, 121006. https://doi.org/10.1088/2515-7620/acab4f

Gao, Q., Guo, Y., Xu, H., Ganjurjav, H., Li, Y., Wan, Y., Qin, X., Ma, X., Liu, S., 2016a. Climate change and its impacts on vegetation distribution and net primary productivity of the alpine ecosystem in the Qinghai-Tibetan Plateau. Sci. Total Environ. 554–555, 34–41. https://doi.org/10.1016/j.scitotenv.2016.02.131

Gao, Q., Zhu, W., Schwartz, M.W., Ganjurjav, H., Wan, Y., Qin, X., Ma, X., Williamson, M.A., Li, Y., 2016b. Climatic change controls productivity variation in global grasslands. Sci. Rep. 6, 26958. https://doi.org/10.1038/srep26958

George, M., Lile, D., 2009. Stocking rate and carrying capacity. Module 4: Ranch operations and grazing management.

Godde, C.M., Boone, R.B., Ash, A.J., Waha, K., Sloat, L.L., Thornton, P.K., Herrero, M., 2020. Global rangeland production systems and livelihoods at threat under climate change and variability. Environ. Res. Lett. 15, 044021. https://doi.org/10.1088/1748-9326/ab7395

Hauser, M., Engelbrecht, F., Fischer, E. M., 2022. Transient global warming levels for CMIP5 and CMIP6. https://doi.org/10.5281/ZENODO.7390473

Havlík, P., Leclère, D., Valin, H., Herrero, M., Schmid, E., Soussana, J.F., Mueller, C., Obersteiner, M., 2015. Global climate change, food supply and livestock production systems: A bioeconomic analysis, in: Climate Change and Food Systems: Global Assessments and Implications for Food Security and Trade. FAO, pp. 178–197.

Havlík, P., Valin, H., Herrero, M., Obersteiner, M., Schmid, E., Rufino, M.C., Mosnier, A., Thornton, P.K., Böttcher, H., Conant, R.T., Frank, S., Fritz, S., Fuss, S., Kraxner, F., Notenbaert, A., 2014. Climate change mitigation through livestock system transitions. Proc. Natl. Acad. Sci. 111, 3709–3714. https://doi.org/10.1073/pnas.1308044111

Herrero, M., Grace, D., Njuki, J., Johnson, N., Enahoro, D., Silvestri, S., Rufino, M.C., 2013. The roles of livestock in developing countries. Animal 7, 3–18. https://doi.org/10.1017/S1751731112001954

Herrero, M., Havlík, P., Valin, H., Notenbaert, A., Rufino, M.C., Thornton, P.K., Blümmel, M., Weiss, F., Grace, D., Obersteiner, M., 2013. Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. Proc. Natl. Acad. Sci. 110, 20888–20893. https://doi.org/10.1073/pnas.1308149110

Herrero, M., Thornton, P.K., 2013. Livestock and global change: Emerging issues for sustainable food systems. Proc. Natl. Acad. Sci. 110, 20878–20881. https://doi.org/10.1073/pnas.1321844111

Herrero, M., Thornton, P.K., Gerber, P., Reid, R.S., 2009. Livestock, livelihoods and the environment: understanding the trade-offs. Curr. Opin. Environ. Sustain. 1, 111–120. https://doi.org/10.1016/j.cosust.2009.10.003

Hufkens, K., Keenan, T.F., Flanagan, L.B., Scott, R.L., Bernacchi, C.J., Joo, E., Brunsell, N.A., Verfaillie, J., Richardson, A.D., 2016. Productivity of North American grasslands is increased under future climate scenarios despite rising aridity. Nat. Clim. Change 6, 710–714. https://doi.org/10.1038/nclimate2942

Hui, D., Jackson, R.B., 2006. Geographical and interannual variability in biomass partitioning in grassland ecosystems: a synthesis of field data. New Phytol. 169, 85–93. https://doi.org/10.1111/j.1469-8137.2005.01569.x

Huntingford, C., Oliver, R.J., 2021. Constraints on estimating the CO2 fertilization effect emerge. Nature 600, 224–225. https://doi.org/10.1038/d41586-021-03560-w

Ipcc, 2022. Global Warming of 1.5°C: IPCC Special Report on Impacts of Global Warming of 1.5°C above Pre-industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to Eradicate Poverty, 1st ed. Cambridge University Press. https://doi.org/10.1017/9781009157940

Kolby Smith, W., Reed, S.C., Cleveland, C.C., Ballantyne, A.P., Anderegg, W.R.L., Wieder, W.R., Liu, Y.Y., Running, S.W., 2016. Large divergence of satellite and Earth system model estimates of global terrestrial CO2 fertilization. Nat. Clim. Change 6, 306–310. https://doi.org/10.1038/nclimate2879

Kwon, H.-Y., Nkonya, E., Johnson, T., Graw, V., Kato, E., Kihiu, E., 2016. Global Estimates of the Impacts of Grassland Degradation on Livestock Productivity from 2001 to 2011, in: Nkonya, E., Mirzabaev, A., Von Braun, J. (Eds.), Economics of Land Degradation and Improvement – A Global Assessment for Sustainable Development. Springer International Publishing, Cham, pp. 197–214. https://doi.org/10.1007/978-3-319-19168-3_8

Lange, S., Büchner, M., 2017. ISIMIP2b bias-adjusted atmospheric climate input data. https://doi.org/10.48364/ISIMIP.208515

Li, S., Lü, S., Zhang, Y., Liu, Y., Gao, Y., Ao, Y., 2015. The change of global terrestrial ecosystem net primary productivity (NPP) and its response to climate change in CMIP5. Theor. Appl. Climatol. 121, 319–335. https://doi.org/10.1007/s00704-014-1242-8

Liang, J., Xia, J., Liu, L., Wan, S., 2013. Global patterns of the responses of leaf-level photosynthesis and respiration in terrestrial plants to experimental warming. J. Plant Ecol. 6, 437–447. https://doi.org/10.1093/jpe/rtt003

Lin, H., Wang, X., Zhang, Y., Liang, T., Feng, Q., Ren, J., 2013. Spatio-temporal dynamics on the distribution, extent, and net primary productivity of potential grassland in response to climate changes in China. Rangel. J. 35, 409. https://doi.org/10.1071/RJ12024

Michalk, D.L., Kemp, D.R., Badgery, W.B., Wu, J., Zhang, Y., Thomassin, P.J., 2019. Sustainability and future food security-A global perspective for livestock production. Land Degrad. Dev. 30, 561–573. https://doi.org/10.1002/ldr.3217

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., Van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P., Wilbanks, T.J., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747–756. https://doi.org/10.1038/nature08823

O'Mara, F.P., 2012. The role of grasslands in food security and climate change. Ann. Bot. 110, 1263–1270. https://doi.org/10.1093/aob/mcs209

Ostberg, S., Schewe, J., Childers, K., Frieler, K., 2018. Changes in crop yields and their variability at different levels of global warming. Earth Syst. Dyn. 9, 479–496. https://doi.org/10.5194/esd-9-479-2018

Pan, Y., Jackson, R.B., Hollinger, D.Y., Phillips, O.L., Nowak, R.S., Norby, R.J., Oren, R., Reich, P.B., Lüscher, A., Mueller, K.E., Owensby, C., Birdsey, R., Hom, J., Luo, Y., 2022. Contrasting responses of woody and grassland ecosystems to increased CO2 as water supply varies. Nat. Ecol. Evol. 6, 315–323. https://doi.org/10.1038/s41559-021-01642-6

Petz, K., Alkemade, R., Bakkenes, M., Schulp, C.J.E., van der Velde, M., Leemans, R., 2014. Mapping and modelling trade-offs and synergies between grazing intensity and ecosystem services in rangelands using global-scale datasets and models. Glob. Environ. Change 29, 223–234. https://doi.org/10.1016/j.gloenvcha.2014.08.007

Piipponen, J., Jalava, M., de Leeuw, J., Rizayeva, A., Godde, C., Cramer, G., Herrero, M., Kummu, M., 2022. Global trends in grassland carrying capacity and relative stocking density of livestock. Glob. Change Biol. 28, 3902–3919. https://doi.org/10.1111/gcb.16174

Piipponen, J., Jalava, M., de Leeuw, J., Rizayeva, A., Godde, C., Cramer, G., Herrero, M., Kummu, M., 2022. Data for "Global trends in grassland carrying capacity and relative stocking density of livestock." https://doi.org/10.5281/ZENODO.6366896

Puche, N.J.B., Kirschbaum, M.U.F., Viovy, N., Chabbi, A., 2023. Potential impacts of climate change on the productivity and soil carbon stocks of managed grasslands. PLOS ONE 18, e0283370. https://doi.org/10.1371/journal.pone.0283370

Qian, S., Wang, L.Y., Gong, X.F., 2012. Climate change and its effects on grassland productivity and carrying capacity of livestock in the main grasslands of China. Rangel. J. 34, 341. https://doi.org/10.1071/RJ11095

Quan, Q., Zhang, F., Meng, C., Ma, F., Zhou, Q., Sun, F., Niu, S., 2020. Shifting biomass allocation determines community water use efficiency under climate warming. Environ. Res. Lett. 15, 094041. https://doi.org/10.1088/1748-9326/aba472

Reyer, C., Chang, J., Chen, M., Forrest, M., François, L., Henrot, A.-J., Hickler, T., Ito, A., Nishina, K., Ostberg, S., Schaphoff, S., Seneviratne, S.I., Shi, H., Steinkamp, J., Thiery, W., Tian, H., Zhao, F., Büchner, M., Ciais, P., 2019. ISIMIP2b Simulation Data from Biomes Sector. https://doi.org/10.5880/PIK.2019.012

Reyes-Fox, M., Steltzer, H., Trlica, M.J., McMaster, G.S., Andales, A.A., LeCain, D.R., Morgan, J.A., 2014. Elevated CO2 further lengthens growing season under warming conditions. Nature 510, 259–262. https://doi.org/10.1038/nature13207

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Glob. Environ. Change 42, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Roy, J., Picon-Cochard, C., Augusti, A., Benot, M.-L., Thiery, L., Darsonville, O., Landais, D., Piel, C., Defossez, M., Devidal, S., Escape, C., Ravel, O., Fromin, N., Volaire, F., Milcu, A., Bahn, M., Soussana, J.-F., 2016. Elevated CO_2 maintains grassland net carbon uptake under a future heat and drought extreme. Proc. Natl. Acad. Sci. 113, 6224–6229. https://doi.org/10.1073/pnas.1524527113

Scheiter, S., Langan, L., Higgins, S.I., 2013. Next-generation dynamic global vegetation models: learning from community ecology. New Phytol. 198, 957–969. https://doi.org/10.1111/nph.12210

Seibert, R., Donath, T.W., Moser, G., Laser, H., Grünhage, L., Schmid, T., Müller, C., 2021. Effects of long-term CO2 enrichment on forage quality of extensively managed temperate grassland. Agric. Ecosyst. Environ. 312, 107347. https://doi.org/10.1016/j.agee.2021.107347

Seneviratne, S.I., X. Zhang, M. Adnan, W. Badi, C. Dereczynski, A. Di Luca, S. Ghosh, I. Iskandar, J. Kossin, S. Lewis, F. Otto, I. Pinto, M. Satoh, S.M. Vicente-Serrano, M. Wehner, and B. Zhou, 2021: Weather and Climate Extreme Events in a Changing Climate. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change[Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1513–1766, doi: 10.1017/9781009157896.013., n.d.

Sexton, J.O., Song, X.-P., Feng, M., Noojipady, P., Anand, A., Huang, C., Kim, D.-H., Collins, K.M., Channan, S., DiMiceli, C., Townshend, J.R., 2013. Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS vegetation continuous fields with lidar-based estimates of error. Int. J. Digit. Earth 6, 427–448. https://doi.org/10.1080/17538947.2013.786146

Sun, Y., Feng, Y., Wang, Y., Zhao, X., Yang, Y., Tang, Z., Wang, S., Su, H., Zhu, J., Chang, J., Fang, J., 2021a. Field-Based Estimation of Net Primary Productivity and Its Above- and Belowground Partitioning in Global Grasslands. J. Geophys. Res. Biogeosciences 126. https://doi.org/10.1029/2021JG006472

Sun, Y., Yang, Y., Zhao, X., Tang, Z., Wang, S., Fang, J., 2021b. Global patterns and climatic drivers of above- and belowground net primary productivity in grasslands. Sci. China Life Sci. 64, 739–751. https://doi.org/10.1007/s11427-020-1837-9

Tian, C., Yue, X., Zhou, H., Lei, Y., Ma, Y., Cao, Y., 2021. Projections of changes in ecosystem productivity under 1.5 °C and 2 °C global warming. Glob. Planet. Change 205, 103588. https://doi.org/10.1016/j.gloplacha.2021.103588

Tietjen, B., Jeltsch, F., Zehe, E., Classen, N., Groengroeft, A., Schiffers, K., Oldeland, J., 2009. Effects of climate change on the coupled dynamics of water and vegetation in drylands. Ecohydrology n/a-n/a. https://doi.org/10.1002/eco.70

Umuhoza, J., Jiapaer, G., Yin, H., Mind'je, R., Gasirabo, A., Nzabarinda, V., Umwali, E.D., 2021. The analysis of grassland carrying capacity and its impact factors in typical mountain areas in Central Asia—A case of Kyrgyzstan and Tajikistan. Ecol. Indic. 131, 108129. https://doi.org/10.1016/j.ecolind.2021.108129

White, R.P., Murray, S., Rohweder, M., 2000. Pilot analysis of global ecosystems: grassland ecosystems. World Resources Institute, Washington, DC.

Wieder, W.R., Cleveland, C.C., Smith, W.K., Todd-Brown, K., 2015. Future productivity and carbon storage limited by terrestrial nutrient availability. Nat. Geosci. 8, 441–444. https://doi.org/10.1038/ngeo2413

Wolf, J., Chen, M., Asrar, G.R., 2021. Global Rangeland Primary Production and Its Consumption by Livestock in 2000–2010. Remote Sens. 13, 3430. https://doi.org/10.3390/rs13173430

Wu, G., Cheng, Z., Alatalo, J.M., Zhao, J., Liu, Y., 2021. Climate Warming Consistently Reduces Grassland Ecosystem Productivity. Earths Future 9. https://doi.org/10.1029/2020EF001837

Zarei, A., Chemura, A., Gleixner, S., Hoff, H., 2021. Evaluating the grassland NPP dynamics in response to climate change in Tanzania. Ecol. Indic. 125, 107600. https://doi.org/10.1016/j.ecolind.2021.107600

Zhang, H., Fan, J., Wang, J., Cao, W., Harris, W., 2018. Spatial and temporal variability of grassland yield and its response to climate change and anthropogenic activities on the Tibetan Plateau from 1988 to 2013. Ecol. Indic. 95, 141–151. https://doi.org/10.1016/j.ecolind.2018.05.088

Appendix

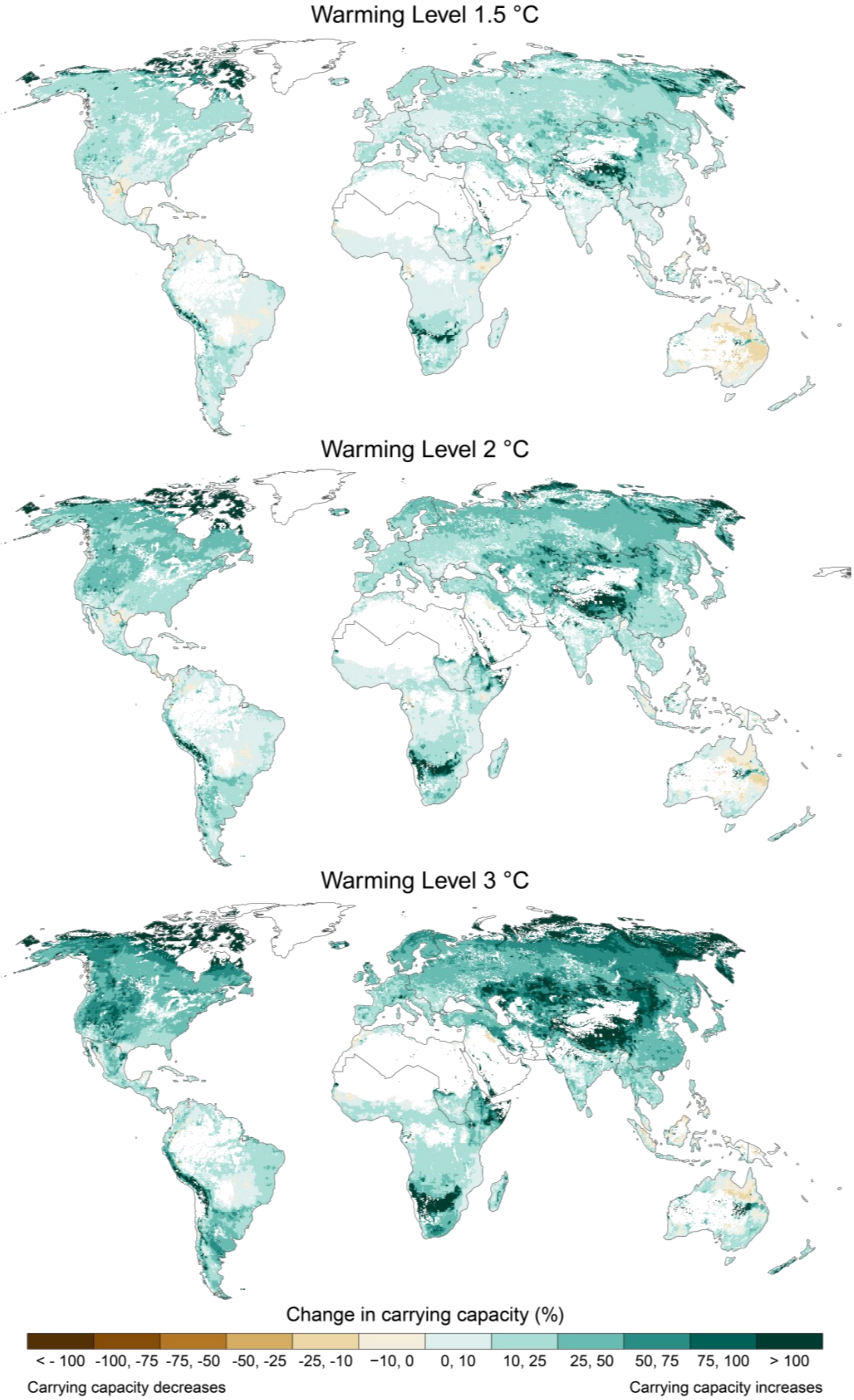

Figure 24. Relative change of carrying capacity (%) according to the models ensemble. Each map represents the change for future scenarios expressed as warming levels (mean over 20 years periods) from a baseline period (mean of 2006-2015).

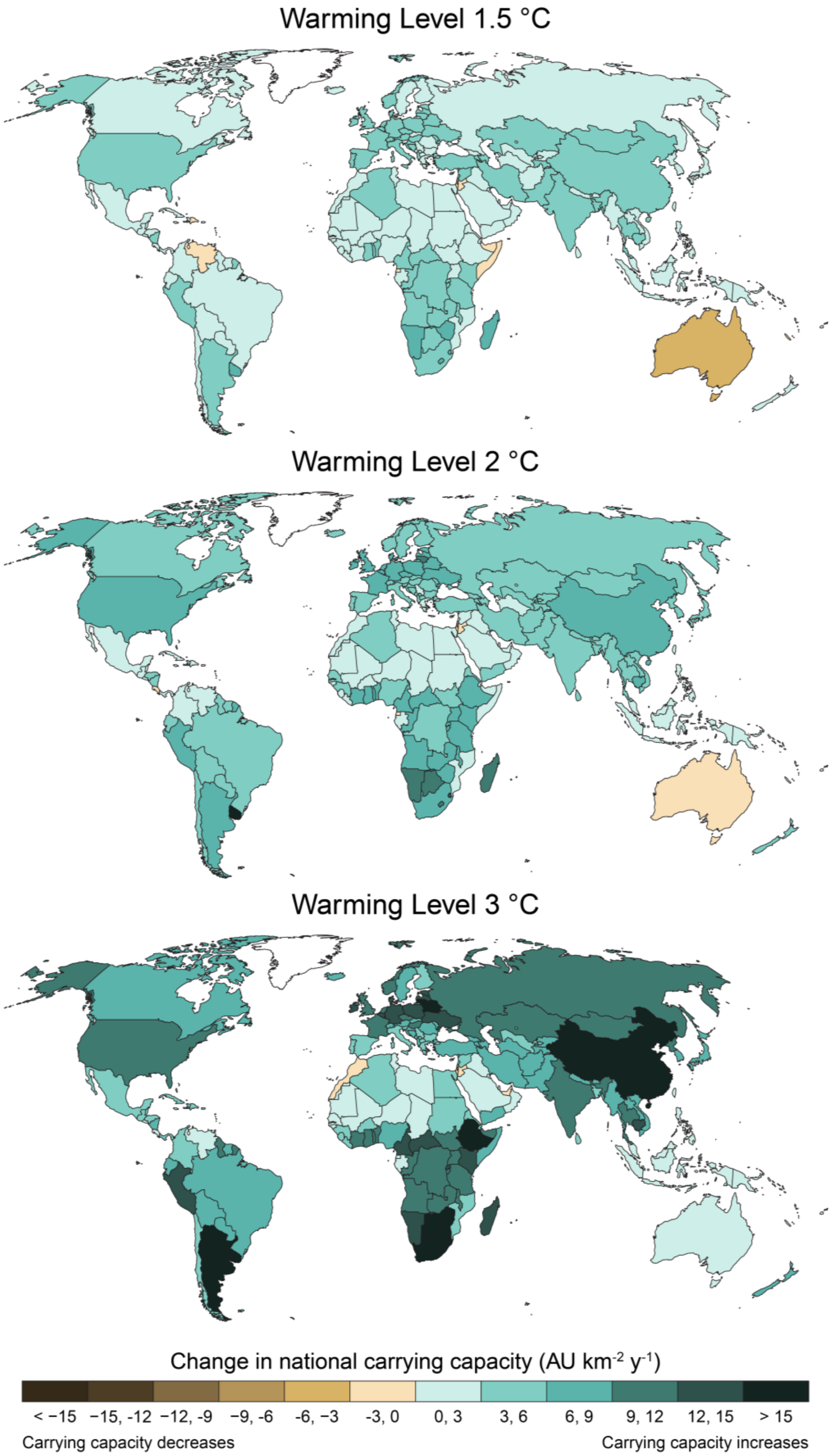

Figure 25. Absolute change of national carrying capacity (AU km^{-2} y^{-1}) according to the models ensemble. Each map represents the change for future scenarios expressed as warming levels (mean over 20 years periods) from a baseline period (mean of 2006-2015).

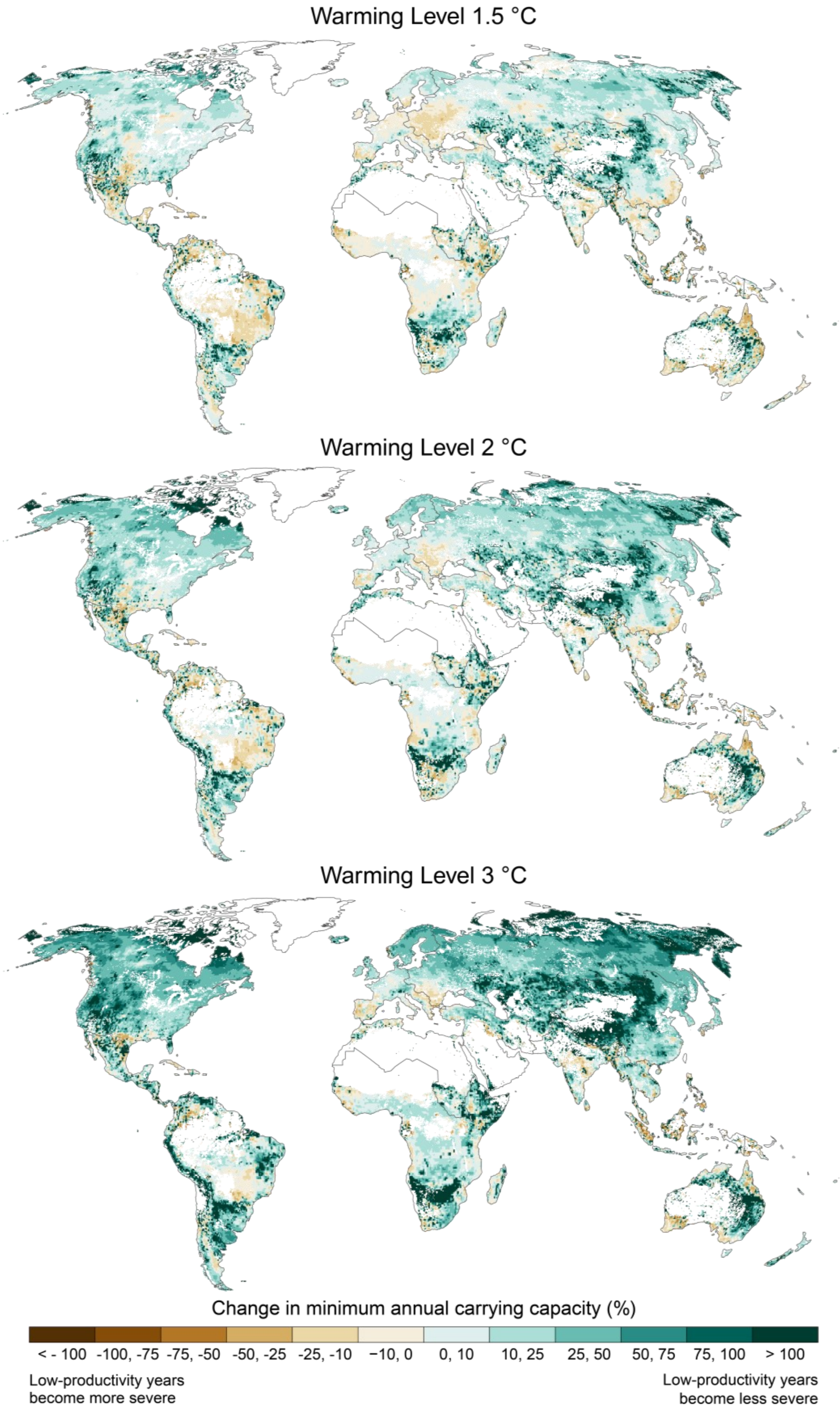

Figure 26. Relative change of minimum annual carrying capacity (%) according to the models ensemble. Each map represents the change of annual minimums for future scenarios (minimum of the 20 years periods indicating a specific warming level) from a baseline period (minimum of 2006-2015).

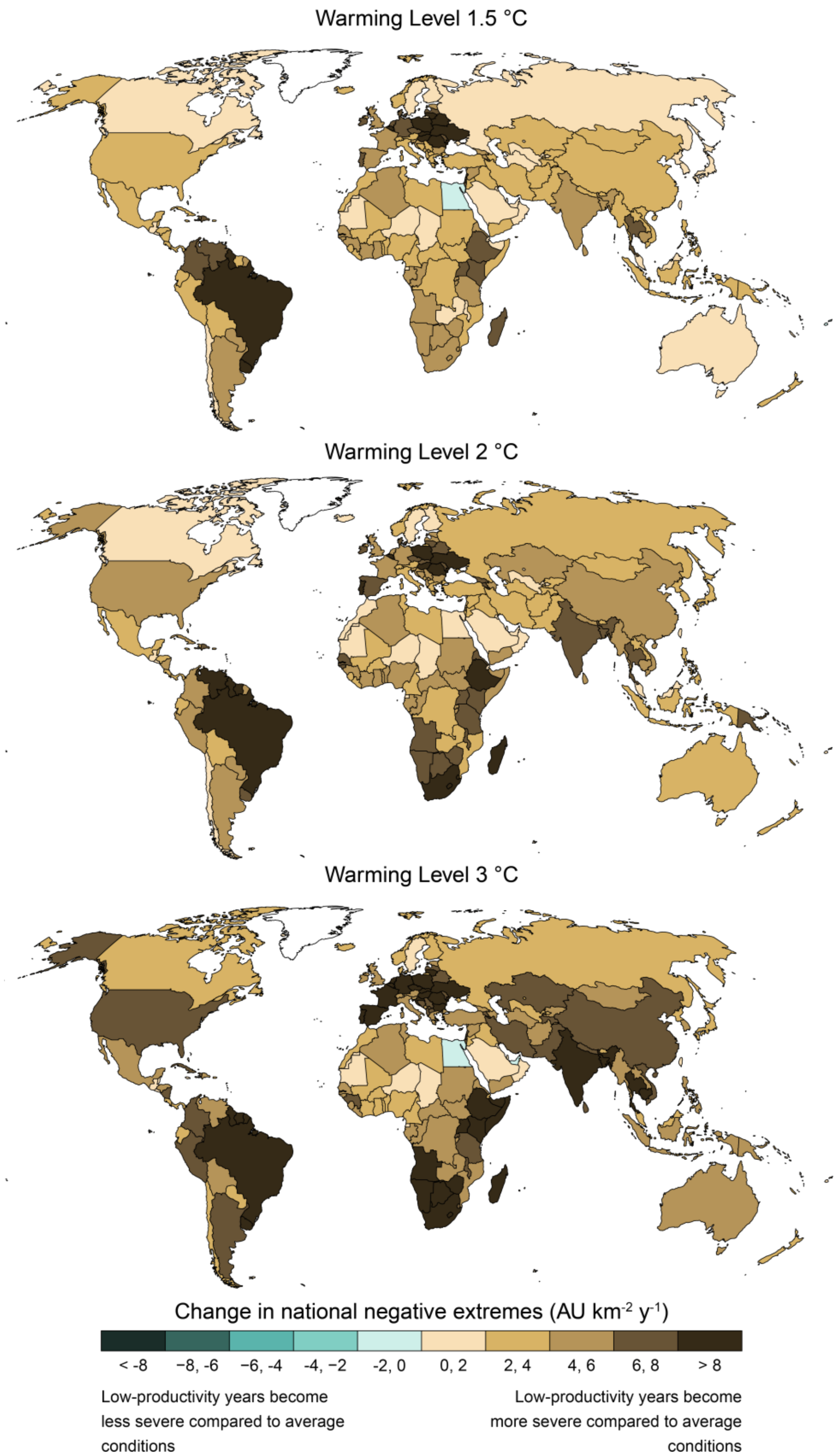

Figure 27. Absolute change (AU km^{-2} y^{-1}) of national negative extremes (difference between the average and minimum annual carrying capacity of a specific time period) according to the models ensemble. Each map indicates how much the difference between average and minimum annual carrying capacity of future scenarios will change from the existing differences of the period 2006-2015.

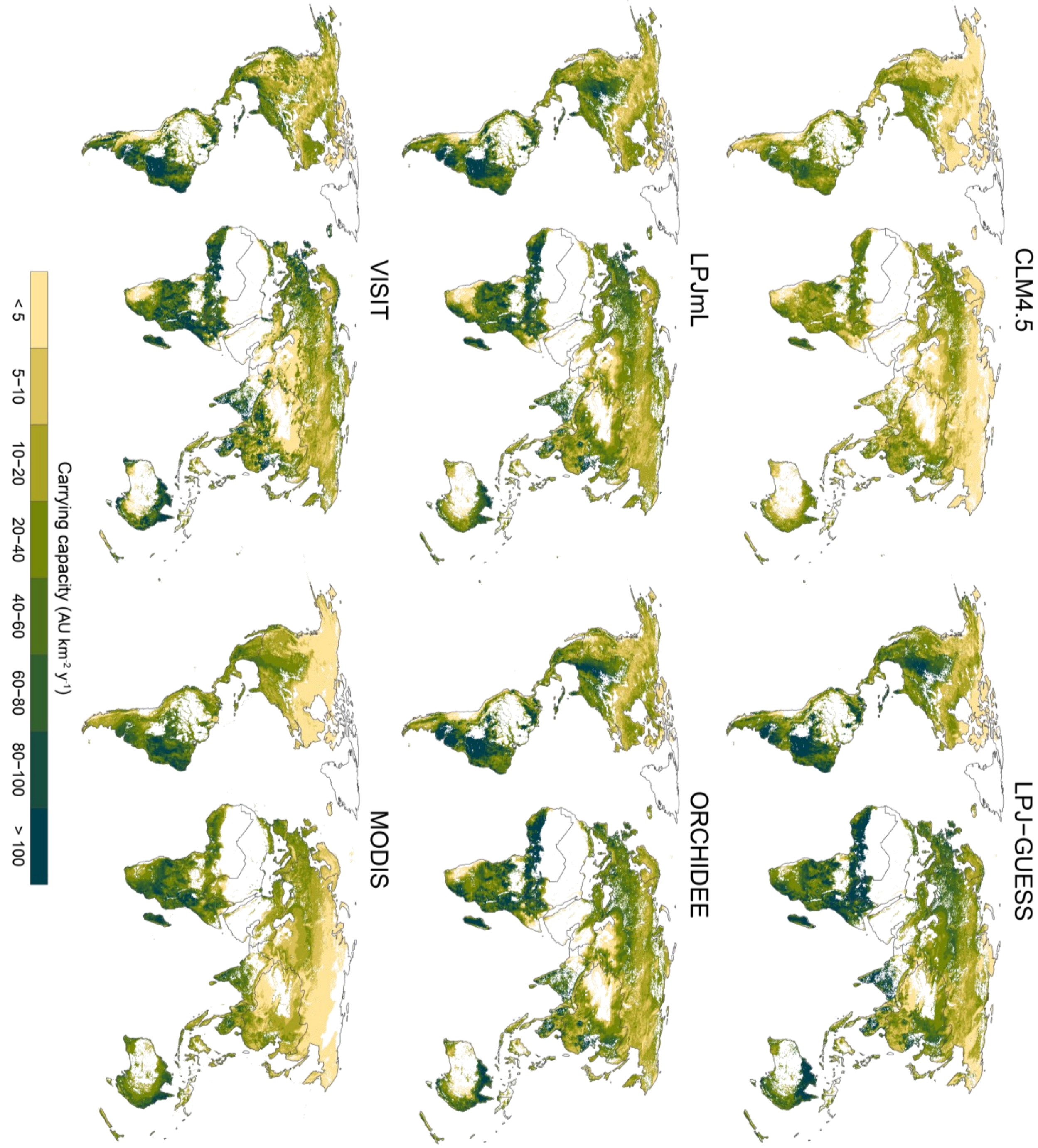

Figure 28. Carrying capacity (CC) estimations (AU km^{-2} y^{-1}) for the period 2006-2015 according to each vegetation model (VM) adopted in the analysis. They represent the average of the four different CC estimations produced by the same VM when forced by the four different general circulation models (GCMs) for that specific time period. MODIS data were retrieved from Piipponen et al. (2022).

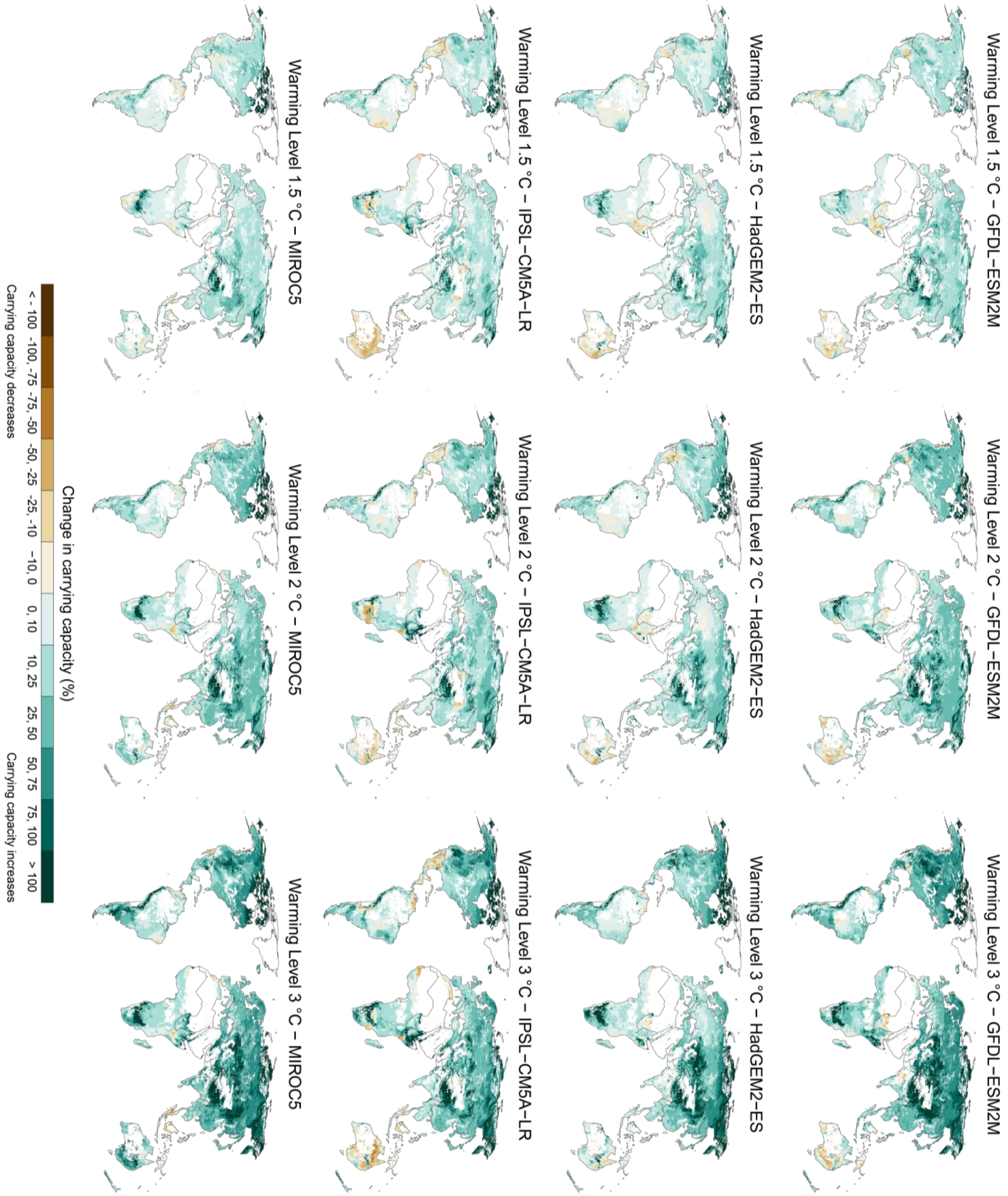

Figure 29. Relative change of carrying capacity (%) according to each models ensemble based on the forcing general circulation model (GCM). Each map represents the change for future scenarios expressed as warming levels (mean over 20 years periods) from a baseline period (mean of 2006-2015).

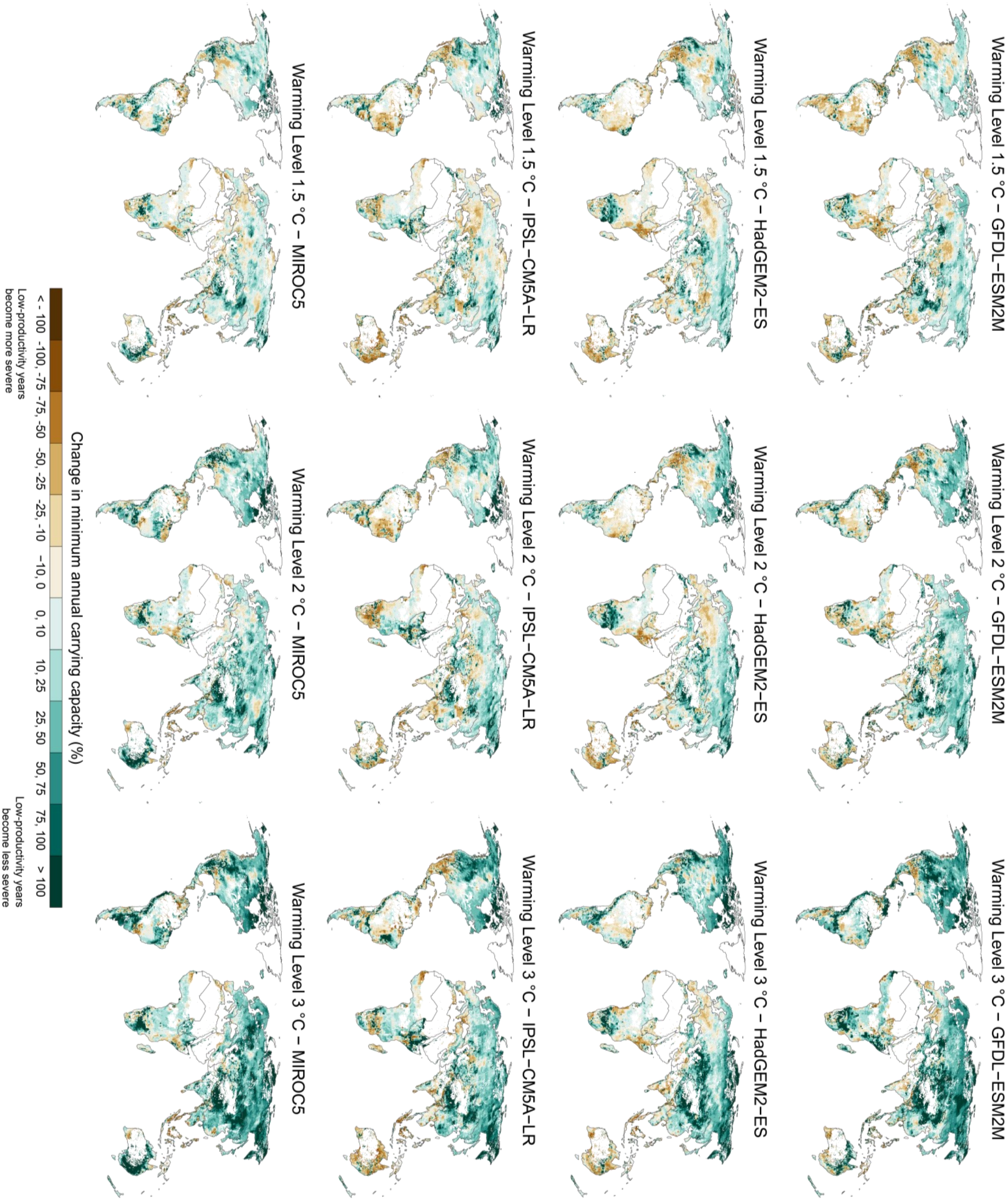

Figure 30. Relative trends of minimum annual carrying capacity (%) according to each models ensemble based on the forcing general circulation model (GCM). Each map represents the change for future scenarios expressed as warming levels (20 years periods) from a baseline period (2006-2015).

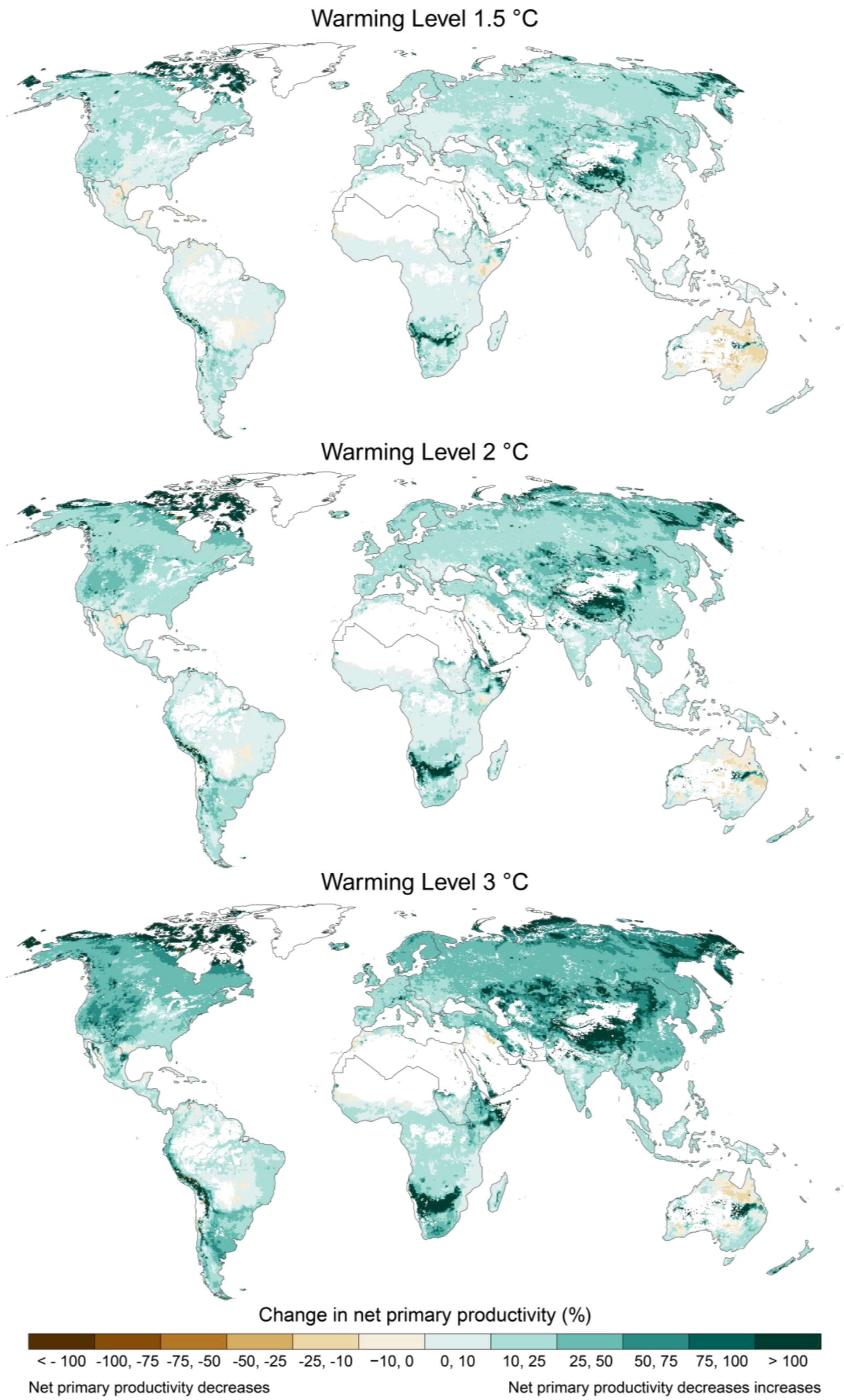

Figure 31. Relative change of net primary productivity (%) according to the models ensemble. Each map represents the change for future scenarios expressed as warming levels (mean over 20 years periods) from a baseline period (mean of 2006-2015).

Table 12. Change of net primary productivity (NPP) of global grasslands according to each model combination.

		Global net primary productivity change (%)		
Vegetation Model	**General Circulation Model**	**Warming Level 1.5 °C**	**Warming Level 2°C**	**Warming Level 3°C**
CLM4.5	GFDL-ESM2M	4.0%	7.8%	13.1%
CLM4.5	HadGEM2-ES	3.3%	4.9%	8.5%
CLM4.5	IPSL-CM5A-LR	2.9%	5.0%	9.1%
CLM4.5	MIROC5	4.1%	7.8%	13.6%
LPJ-GUESS	GFDL-ESM2M	9.6%	17.0%	29.7%
LPJ-GUESS	HadGEM2-ES	5.9%	10.3%	18.8 %
LPJ-GUESS	IPSL-CM5A-LR	6.5%	11.1%	20.0%
LPJ-GUESS	MIROC5	9.0%	15.8%	27.4%
LPJmL	GFDL-ESM2M	9.4%	17.6%	31.7%
LPJmL	HadGEM2-ES	4.9%	8.8%	17.2%
LPJmL	IPSL-CM5A-LR	5.9%	9.6%	18.5%
LPJmL	MIROC5	9.0%	16.7%	31.2%
ORCHIDEE	GFDL-ESM2M	13.6%	23.5%	40.5%
ORCHIDEE	HadGEM2-ES	8.0%	13.7%	24.2%
ORCHIDEE	IPSL-CM5A-LR	8.5%	14.4%	24.8%
ORCHIDEE	MIROC5	12.3%	22.1%	37.3%
VISIT	GFDL-ESM2M	7.3%	13.3%	25.6%
VISIT	HadGEM2-ES	4.9%	8.2%	14.3%
VISIT	IPSL-CM5A-LR	5.4%	9.1%	16.0%
VISIT	MIROC5	8.4%	14.7%	25.7%
Models ensemble		7.1%	12.6%	22.4%