Between Nature and Nourishment

Evaluating the impact of climate justice principles on terrestrial carbon storage and agricultural land use

Written by: Gerard van Smeden

Between Nourishment and Nature

Evaluating the impact of Climate Justice principles on agricultural land use and terrestrial carbon storage

By

Gerard van Smeden

in partial fulfillment of the requirements for the degree of

Master of Science
in Engineering and Policy Analysis

at the Delft University of Technology,
to be defended publicly on Wednesday, June 28, 2023, at 9:30 AM.

Full name:	Gerard van Smeden		
Student number:	4552202		
Faculty:	Technology, Policy, and Management		
Thesis committee:	Prof. Dr. ir. J. (Jan) Kwakkel	TU Delft	Chair
	Dr. ir. W. L. (Willem) Auping	TU Delft	First supervisor
	Prof. Dr. ir. B. (Behnam) Taebi	TU Delft	Second supervisor

Preface

With this thesis comes and end to my journey at the TU Delft. I am most grateful for the way that I have learned to analyze complex systems and try to find high-impact improvements. Although I have learned to build computer models, I also become much better at mental modeling. I am grateful that I got to apply my knowledge next to my studies in several work experiences, such as when building Building Blocks at De Energiebespaarders, starting my first business Droomdiner and now with my start-up Unifix Care. Working full time after studying and graduation has led to me not being as present with friends and family all the time, but I still see the great relationships I have developed.

Specifically, I want to thank my supervisor Willem Auping for supporting me during this long journey, keeping me motivated, and being thoughtful about my struggles. Some meetings have been more on a personal level than on the thesis content, and that is something I highly appreciate. Additionally, I want to thank my father, Broer van Smeden, for regularly checking in with me, trying to support me in any way possible, and being a sparring partner throughout my thesis. Lastly, all other supervisors, friends, family, and colleagues have supported me throughout the journey.

Gerard van Smeden
Delft, June 2023

Contents

Management summary

Terrestrial carbon storage presents an opportunity that policymakers must consider in the fight against climate change. Carbon sequestration and storage potential - specifically in our forests and wetlands - is immense; the average difference between entirely neglecting or integrating it in policy is 3,68 degrees Celsius or 1085 GtC. This thesis explores this significance and points toward prioritizing ecosystem conservation as a highly effective strategy for mitigating climate change. Initiatives such as carbon offsetting, performed by organizations like '*8 billion trees*' and '*cool earth*', could provide feasible solutions to enhance carbon sequestration. The EU's Nature Restoration Law is a step in the right direction, advocating for the conservation of existing ecosystems and restoring deteriorated systems, specifically increasing organic stocks in forests and restoring and rewetting drained peatlands of agricultural use and peat extraction sites seem to be compelling aspects in terms of improving the carbon system proposed in this law. I encourage the exploration of similar policy changes globally, underscoring the importance of taking immediate action and ensuring no further deterioration of existing terrestrial carbon systems.

Following the importance of terrestrial carbon storage, the debate remains about who should sacrifice their land. This research has displayed a high sensitivity in land allocation for terrestrial carbon storage when comparing ethical perspectives of justness, also defined as climate justice principles. This sensitivity can be seen as normative uncertainties and represent potential tensions in developing a coherent global policy. In my research, certain countries are more sensitive to these normative uncertainties than others. The Netherlands, Pakistan, China, and Yemen are highly sensitive to terrestrial carbon storage obligations if islands and smaller states are not considered. In the case of the Netherlands, this sensitivity is caused by a high GDP and, therefore, ability-to-pay. Still, when following efficiency prioritized, Dutch agricultural land should be kept for its high agricultural productivity. China is expected to reach a high level of domestic food security. Therefore, they would have to sacrifice their land for terrestrial carbon storage according to a different interpretation of ability-to-pay. Also, the efficiency prioritized principle for China would be ideal because, with their economic growth and innovation, they are expected to reach a high level of agricultural productivity. In the case of Yemen, it is different, Yemen has low agricultural productivity, and efficiency-prioritized will lead to them converting agricultural land to forests. The best interpretation of ability-to-pay for Yemen is the available land that could be converted for terrestrial carbon storage.

In my analysis, I showed proof of principle to include these normative uncertainties in policy analysis to explore areas of consensus. Through this approach, I found countries that should convert or conserve their land for terrestrial carbon storage and countries that arguably could still replace their forests and wetlands for other land covers such as urban- and agricultural land. I propose that climate justice principles should be included as uncertainties in policy-analysis, thus arguing for – additional – simplified models to allow for easy implementation of these uncertainties in the analysis.

To come to these findings, I performed an extensive analysis of the global food-, land cover-, and carbon system, simulating a wide range of scenarios up to the year 2100. The model I have developed operates at a national-detail level and includes 173 countries worldwide. The model considers several factors for each country, such as socioeconomic development, current land cover, agricultural productivity, and food demand. The national systems interact globally to represent global systems such as food change and the carbon cycle.

I tested a wide range of distribution methods on this system for terrestrial carbon storage burden, represented by five policy levers. Additionally, I considered 21 uncertainties in the model and performed 10.000 experiments to ensure the robustness of the proposed policies. In the last phase of the analysis, I created world maps that display the land countries should convert for terrestrial carbon storage according to climate justice principles and the sensitivity per country. These maps allow for an easy understanding and interpretation of the climate justice principles.

I started the research by exploring frequently used climate change policy evaluation in ethics. Ethics literature discusses two main social justice types: distributive and procedural justice. In this study, I focus on distributive justice for its applicability in modelling solutions. I utilize pre-defined climate justice principles and introduce a new principle – efficiency prioritized, based on the utilitarian principle. The '*principle efficiency prioritized*' allocates agricultural land to countries with the highest agricultural productivity and terrestrial carbon storage burden to the less-productive countries. Selected principles are Ability to Pay (based on available land for terrestrial carbon storage, domestic food supply, and GDP per capita), You-Broke-It-You-Fix-It (based on historical emissions), and Efficiency Prioritized, with different interpretation methods considered for Ability to Pay.

I modeled the system using Vensim, a System Dynamics modeling software. System Dynamics is a quantitative modeling formalism suitable for dealing with complex systems, allowing for exploring relations between system structure and behavior. It helps to understand the complex land use, land-use change, and forestry, food, and carbon system. It also enables the incorporation of parametric and structural uncertainties, testing a wide range of scenarios in systems with deep uncertainty. The model consists of several sub-systems, leveraging existing models from prior research by Auping (2018), and takes data from sources such as the World Bank, FAOSTAT, OECD, and IPCC as input.

To find robust policies in the face of deep uncertainty, I adopted an Exploratory Modelling and Analysis (EMA) approach using the open-source EMA workbench for Python. This approach involves performing a broad range of computational experiments, analyzing the results, and identifying robust policies based on these findings. EMA workbench has a special connection built-in to run experiments with Vensim efficiently. It includes built-in functions for sampling, such as Latin Hypercube Sampling, and scenario discovery, such as PRIM, used in my analysis to find the scenarios of interest.

I visualized the results with Basemap, NumPy, Pandas, and the EMA workbench, among other tools. Creating maps allows for a simple data representation, enhancing understanding and communicating the findings. This approach enables a thorough exploration of climate justice principles, modeling, and experimentation, providing valuable insights for decision-makers facing complex and uncertain climate change challenges.

To summarize, I applied System Dynamics modeling and scenario discovery to explore the global food and carbon system. I proved the importance of terrestrial carbon storage, especially conserving existing forests and wetlands. Terrestrial carbon storage policy also faces policy challenges in implementation, mainly the distribution of the terrestrial carbon storage burden. Because land for terrestrial carbon storage goes at the cost of agricultural and urban land that could provide economic prosperity and food security, there is a trade-off between different Sustainable Development Goals. Several distribution conventions have been evaluated following climate justice principles to find overlapping policies between the principles. I found a significant difference in the distribution of terrestrial carbon storage obligations between the principles, displaying potential complexities and tensions in policy-making. I also found consensus between the principles, defined as non-discriminatory policies. Policy-makers should start with non-discriminatory policies to ensure swift implementation. I recommend that other policy modelers also include ethical perspectives as uncertainties in their models to find non-discriminatory policies and, if necessary, develop simplified models to enable this.

1 Introduction

Human-caused atmospheric CO_2 emissions from sources such as fossil fuel combustion and deforestation are the primary driver of climate change (IPCC, 2022). By 2020, the atmospheric CO_2 levels have risen to 50% above pre-industrial levels (since 1750). This CO_2 level rise has caused a more than one degree Celsius temperature increase and substantially impacted existing life on earth (NASA Global Climate, 2022).

To mitigate climate change, policymakers and researchers have been focusing on energy-related CO_2 emissions and industrial processes (van den Berg et al., 2020). However, land use, land-use change, and forestry (LULUCF) have received comparatively little attention as policy instruments, despite their significant role in carbon emissions to the atmosphere and carbon sequestration. Cumulative CO_2 emissions from land-use changes for 1750–2020 were 230 ± 75 GtC, while CO_2 emissions from fossil energy usage have been 460 ± 65 GtC (Friedlingstein et al., 2022). In recent years, there has been increasing attention to the role of land use in climate change mitigation, and the IPCC even dedicated a special report to climate change & land, in which they state that land use and land-use change (LULUCF) have a considerable role in climate mitigation policy (IPCC, 2020).

Emissions related to land use and land-use change are high because terrestrial ecosystems comprising vegetation and soil form one of the earth's most significant carbon reservoirs, with the atmosphere, the oceans, and fossil fuels (Green & Byrne, 2004). The land carbon reservoir consists of soil and biomass, with soil being the largest carbon fraction of the terrestrial carbon storage, containing 1400 GtC, and vegetation accounting for an additional 550GtC (Green & Byrne, 2004; Petrokofsky et al., 2012). Changes in land composition, such as deforestation or afforestation, can lead to significant fluctuations in terrestrial carbon storage, either increasing or decreasing the amount of carbon stored.

The amount of carbon stored in soil and biomass differs substantially per land type. Therefore, a change in the Earth's land composition can cause substantial fluxes in carbon between the atmosphere and the terrestrial system (Ciais et al., 2018). Forests and wetlands are carbon-dense land types, estimated to store 75% to 80% of the world's terrestrial organic carbon (Lal, 2008; Reichstein & Carvalhais, 2019) while occupying only 37% (OECD, 2021; United Nations, 2022) of the total land surface. Peatlands and wetlands have the highest carbon density, storing up to three to five times more carbon than terrestrial forests (Carlowicz, Michael, 2012; Dayathilake et al., 2020). In comparison, arable land, cropland, pastures, and meadows occupy a similar surface as forests and wetlands and store only 15% of the world's terrestrial carbon (Janowiak et al., 2017).

The replacement of high-carbon-containing ecosystems such as wetlands, peatlands, and forests (Yirdaw et al., 2017) by agricultural, urban, and infrastructural areas in the past decades has caused substantial CO_2 emissions (Murdiyarso et al., 2015). Since 1900 AD, over half of the original global wetlands have been drained (Davidson & Davidson, 2014; Erb et al., 2017), and one-third of the estimated worldwide forest area has been converted to farmland (Erb et al., 2017). Meanwhile, urban and infrastructure areas expanded from 33.1 to 71.3 Mha between 1992 and 2015 (Mi et al., 2019), and global agricultural land has grown by 200 Mha (Winkler et al., 2021). The conversion of these ecosystems has released a significant amount of carbon into the atmosphere, exacerbating climate change.

The growing world population, urbanization, and increasing demand for food and energy will exacerbate the demand for agricultural and urban land in the coming decades (Popp et al., 2017). At the same time, the IPCC (2020) estimates that the additional global area needed for climate mitigation measures falls within the range of 109-990 Mha compared to the current situation. Humans already exploit much of the highly productive land (Venter et al., 2016), and the additional land requirements will lead to further competition for land, further straining the balance between terrestrial carbon storage and food supply.

Conflicting interests in land demand can become a source of tension and social unrest if not coordinated accordingly (Niewöhner et al., 2016). Effective governance is crucial to address these conflicts and ensure sustainable land use decisions that account for both food security and climate change mitigation goals. To enhance the success of policy interventions, Hussey and Pittock (2012) suggests considering the systemic link between food production and consumption and land resources more broadly. By understanding and addressing the interconnected nature of these issues, policymakers can design policies to optimize land use while minimizing adverse impacts on terrestrial carbon storage and food supply.

The IPCC emphasizes in their special report on Climate Change and Land (2020) that addressing the current policy knowledge gap requires an improved understanding of the mitigation potential, interplay, and costs, as well as the environmental and socio-economic consequences of land use-based mitigation options such as improved agricultural management, forest conservation, bioenergy production, and afforestation on national, regional, and global scales.

Although there is consensus on the importance of incorporating the socio-economic consequences of land-use-based mitigation measures, only a few climate models integrate these factors into their assessments. Ecosystem models (e.g., Dynamic Global Vegetation Models and crop models) and Earth System Models used for modeling the global carbon cycle do not include socioeconomic factors such as economic development, population growth, consumption, technology, and governance (Argles et al., 2022; Friedlingstein et al., 2022). In contrast, Integrated Assessment Models and dedicated land-use models do not integrate the ecosystem response to climate and land-use change, including yield productivity, vegetation cover, and carbon cycling (IPCC, 2020). Furthermore, assessment models tend to aggregate costs and benefits across all actors and the entire planning horizon, which fails to represent potential unequal distributions (Jafino et al., 2021).

Incorporating climate justice principles is crucial when developing climate change policies, as they ensure fairness, equality, and protection for the most vulnerable populations. Integrating climate justice in policy development acknowledges the various interpretations and perspectives on climate change and its impacts. Considering different justice perspectives and interpretations is particularly important, as countries and policy-makers might perceive the climate justice principle that best serves their context as the most just and preferred option, making developing globally coherent distribution strategies more challenging.

This research addresses this knowledge gap by answering: ***"How to distribute the terrestrial carbon storage burden according to climate justice principles and given future uncertainties?"***

Considering the identified research gaps, the following sub-questions are defined to answer the main research question:

1. How do the food production, land cover, and carbon system interrelate, and how are the socio-economic factors, such as food security, impacted by land-use-based climate mitigation?
2. How would countries have to adjust their land cover to meet terrestrial carbon storage obligations under different climate justice principles?
3. Which countries are most sensitive to variations in climate justice, and where can overlapping consensus be found between these principles?

This study will employ a multi-step research approach to answer these research questions. Firstly, to address the first sub-question, I will combine existing System Dynamics (SD) models of global food consumption from Auping et al. (2018), the global carbon cycle based on information from the IPCC (2018) and enrich them using literature findings to tailor the model to this research's specific goal. After this, I will define policies representing climate justice principles and add them to the model. Subsequently, I will conduct a scenario exploration, varying the most critical uncertainties and different policies based on climate justice principles across 10,000 runs. I will then analyze the outcomes of these runs using the Patient Rule Induction Method (PRIM) to identify scenarios of interest. Finally, I will explore similarities and differences between climate justice principles in land-use policy that can achieve terrestrial carbon storage goals. These findings will form the basis for policy recommendations that I will discuss at the end of the report.

2 Methods

This chapter provides an overview of the theoretical framework applied and the methods used for this research. Firstly, the ethical framework for this analysis is composed, followed by an argumentation on the use of SD and the model structure. Lastly, the analysis method, Exploratory Modeling Analysis EMA is introduced.

2.1. Ethical framework

Climate change and climate change policy involve deeply rooted ethical considerations about the fairness of adaptation and mitigation strategies. The distribution of contributions to climate change and the distribution of experienced climate harm typically do not align (Lamont & Favor, 2017). Therefore, paying specific attention to policy fairness in the design and evaluation process is crucial. Social justice theories can serve as moral guidance when developing policies for climate change (Okereke, 2010; Törnblom & Vermunt, 1999).

Two social justice types are conventional to determine policy fairness in climate change: distributive justice and procedural justice (Jafino et al., 2021). Procedural justice concerns the policy development process and the inclusion of all stakeholders in the decision-making process and project planning (Vermunt & Törnblom, 1996). In the context of climate change, procedural justice considers the degree of transparency, participation, and recognition of people affected by the policy (Schlosberg, 2009). Distributive justice refers to distributing benefits and burdens from a policy between actors (Caney, 2009; Konow, 2001; Lamont & Favor, 2017). Applying distributive justice to the context of climate policy is essential because people's vulnerability to the impact of climate change, their capacity to adapt, and their historical contribution to the problem are often unevenly distributed (Füssel, 2010). This analysis will only consider distributive justice since this type of justice is suitable for modeling analysis (Jafino et al., 2021).

Distributive justice considers three factors: shape, unit, and scope of distribution (Bell et al., 2004; Page, 2007). The shape concerns the distribution method of quantities between actors. Different theorems argue for varying just distribution shapes (Konow, 2001). The utilitarian theorem focuses on the highest sum of individual well-being, and is the most influential in public policy (Jafino et al., 2021). Worst-off, also called Rawls's general view of distributive justice (Jin, 2022), focuses on helping the least advantaged people. Sufficientarianism considers basic rights for everyone that must be guaranteed (Shields, 2012). Egalitarian emphasizes equal treatment across all actors. Everyone should have the same level of goods and burdens (Kolm, 1977; Pazner & Schmeidler, 1978).

The unit refers to the metric distributed across stakeholders (e.g., the unit of justice) and how different units should be compared. Models often implement units as a form a value, such as economic values, biodiversity, social values, or welfare (Jafino et al., 2021).

The scope defines the groups between which the selected unit should be distributed. The two segmentations of scope are intragenerational and intergenerational. Intragenerational justice focuses on the distribution between subjects based on their characteristics. The aggregation level of individuals is important to consider for evaluation and, therefore, the level to which the 'acceptability of policy' can be guaranteed. I will concentrate on partitioning based on location, explicitly aggregating per country (Heyward, 2007; Trindade, 2017). Intergenerational justice considers the distribution of burdens and benefits between generations (Caney, 2009). Evaluating intergenerational justice requires disaggregating performance metrics over time series. Additionally, Taebi (2020) argues that accounting for intergenerational justice necessitates acknowledging that the values of the current generation cannot be assumed to hold for future generations.

Climate justice is a form of justice that offers practical frameworks for both distributive as procedural justice. For distributive justice it offers theories for shaping distribution in the climate change context (Jafino et al., 2021; Okereke, 2010). It defines the ethical responsibilities of stakeholders (Schlosberg & Collins, 2014) and guides the scope, size, and potentially the unit of distributive justice principles. Three main principles can be distinguished for climate justice (Jafino et al., 2021; Okereke, 2010): you-broke-it-you-fix-it, ability to pay, and future emissions. According to the you-broke-it-you-fix-it principle, parties must pay according to their level of (historic) pollution. With the ability to pay principle, the distribution is according to their capacity to make climate mitigation adjustments. The future emissions principle considers the expected future contributions.

I will apply the first two climate justice principles to design and develop policies with morally acceptable outcomes (Konow, 2001; Vermunt & Törnblom, 1996). I omit the future emission principle since the predicted future emissions of a country on a time horizon up to 2100 is sensitive to many uncertain factors. As I explore the context in the year 2100, the you-broke-it-you-fix-it principle also includes future emissions as cumulative emissions.

Additionally, we propose a new climate justice principle: '*efficiency prioritized*.' The efficiency prioritized principle represents the utilitarian approach, minimizing the global scarcity of resources to be distributed. As discussed earlier, there is already a shortage of land to fulfill everyone their needs, and one solution to minimize the shortage would be to distribute according to the efficiency level in producing resources. In the case of efficiency prioritized, there would be a preference for countries with high agricultural productivity to have agricultural land, using the less productive land for terrestrial carbon storage.

The burden for terrestrial carbon storage laid upon a country likely differs substantially per climate justice principle. Different actors may prefer policies based on other principles, and this diversity of moral principles can become a source of contestation among stakeholders (Okereke, 2010). If stakeholders perceive the policy as unjust, this can lead to contestations and deadlocks (Pesch et al., 2017). To avoid these deadlocks, (Jafino et al., 2021) suggest simultaneously exploring multiple moral principles of climate justice when comparing alternative policies. For this reason, this research will seek common ground between these different ethical principles. Such common ground could become non-discriminatory interventions that all stakeholders can agree with.

2.2. System Dynamics

Due to the complexity of the LULUCF, food, and carbon system, mental models are complicated. Therefore simulation is a valuable approach to generate insights to understand the system better. SD builds on the premise that mental simulation of systems that contain feedback, accumulations, and delays is fallible (Forrester, 1961; Sterman, 2000). Therefore, computer simulation is needed to derive conclusions about the behavior that arises from a given structure in a logically consistent way (Lane, 2001). Given the complexity and deep uncertainty surrounding future climate change and socio-economic indicators (Shavazipour et al., 2021), a modeling approach that can handle these challenges is essential.

SD is a quantitative modeling formalism suitable for dealing with complex systems (Forrester, 1961; Sterman, 2000). Central to SD is the focus on using models to explore the link between the system structure and the evolutionary behavior over time arising out of this system structure (Lane, 2000). It helps explore relations between system structure and behavior and gain insights into the system behavior dynamics (Sterman, 2000). Additionally, SD allows the incorporation of parametric and structural uncertainties to test a wide range of scenarios and, therefore, model systems that contain deep uncertainty (D'Alessandro et al., 2020; Kwakkel & Pruyt, 2013; Pruyt, 2007).

SD models consist of stocks and flows, representing accumulation, delays, and feedback in real-world systems (Lane, 2000, 2001; Sterman, 2000). Integral equations define stocks, which are affected by input and output every time step, referred to as flows. Additionally, the model contains several other parameters as constants or auxiliary variables. These variables, stocks, and flows represent positive and negative feedbacks within the system. Due to its visual nature, SD helps create a better understanding of factors influencing each other and how these feedback systems work. Feedback loops and state variables are typically represented using stock/flow diagrams and causal loop diagrams (Lane, 2000, 2001; Sterman, 2000).

The LULUCF and food system have many accumulations, delays, and feedbacks. Accumulation and delays, for example, play an important role in terrestrial carbon uptake because it takes several years for the land cover to ultimately convert to be used for agriculture and several decades for the carbon to accumulate and reach its saturation point in carbon stocked (Green & Byrne, 2004; Lal, 2008; Petrokofsky et al., 2012). Feedbacks are prominent in the food system, where food shortage can lead to increased agricultural development and reduce the deficit of specific types of food (Auping et al., 2018). SD is suitable for modeling such a system.

Additionally, several components in the system, like food consumption, follow nonlinear patterns. On top of that, there are still several uncertainties (structural and parametric) in the design, especially in future states. For example, there are still unknowns on factors influencing anthropogenic carbon fluxes and tipping points. For this reason, the Global Carbon Budget uses 17 Dynamic Global Vegetation Models to understand plausible states better (Friedlingstein et al., 2022). Also, parametric uncertainties are substantial for future projections such as food availability, demand, climate change, yield development, population growth, and income growth (Auping et al., 2018). To get an optimal representation of system behavior, adopting a modeling method that allows incorporating these characteristics is crucial, which System Dynamics is perfectly suitable for.

Therefore, it is unsurprising that SD has been used before in similar research problems and has proven effective in this context. In 1976, J.W. Forrester was the first to build a System Dynamics model that included agriculture and food production (Forrester et al., 1976). In recent years, several scholars such as Kopainsky (2015), Brzezina (2016), Auping, Kwakkel, and Pruyt (2018) have been using SD to model the dynamics of food systems, showing that it is still a relevant analysis method for these types of problems. There are also SD models about the interplay between food and energy crops, such as from Pruyt and de Sitter (2008). More specifically, Muizniecea (2015) used SD to model the social and economic impacts of LULUCF, but this model was not yet operating on a global scale.

As the problem discussed is a complex system to model, finding and adjusting existing SD models will help to develop an extensive model within a limited time scope. Additionally, using previously validated model components will help validate the model and build reliability for policymakers. For this research, I based several sub-systems on the model from Auping, Kwakkel, and Pruyt (2018) and a previously developed model from Willem Auping based on the IPCC report '*The Carbon Cycle and Atmospheric Carbon Dioxide*' (2018). Figure 1 displays the configuration of the submodels that are used.

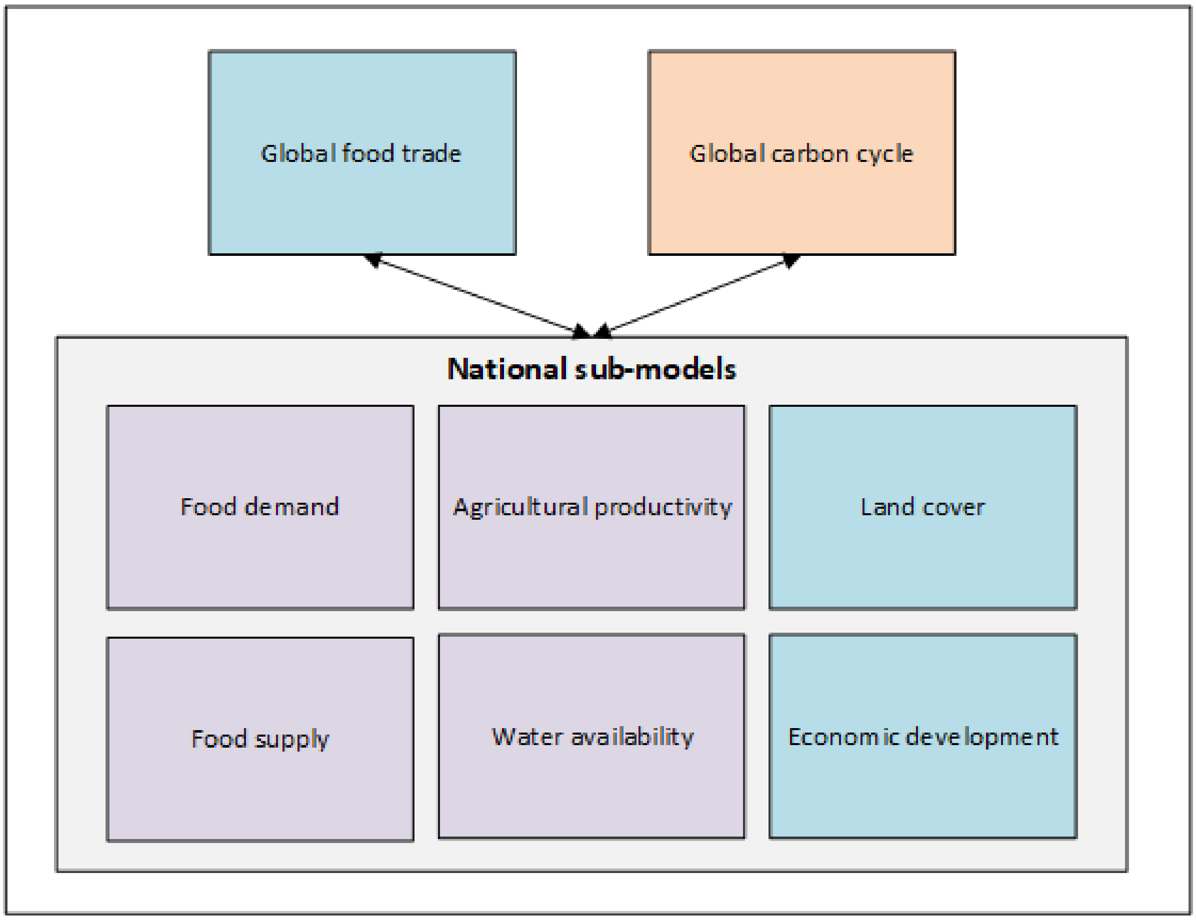


Figure 1 - Model components and integrated sub-models – *Sub-models are represented by rectangles. Purple sub-models are mainly derived from (Auping et al., 2018), orange from Willem Auping based on (IPCC, 2018), blue sub-models, and the connection between national and global sub-models have been the contribution from this research.*

In summary, System Dynamics modeling is well-suited for analyzing the LULUCF, food, and carbon system due to its ability to deal with complexity, deep uncertainty, and the nonlinear nature of the system components. Its focus on stocks and flows enables the representation of real-world accumulation, delays, and feedback, which are integral to understanding these systems. The established success of SD in similar research contexts further supports its applicability to this case, making it an appropriate choice for modeling the dynamics of LULUCF, food, and carbon systems.

2.3. Exploratory Modelling Approach

This research aims to find robust policies while facing deep uncertainty in the LULUCF, food, and carbon system. An EMA approach is followed to account for the impacts of these uncertainties. EMA is a well-recognized approach in the model-based policy analysis literature that supports decision-making under deep uncertainty (Auping, 2018). This approach involves performing a large range of computational experiments, analyzing the results, and identifying robust policies based on these findings (Bankes, 1993). Exploratory System Dynamics helps to better understand the system, specifically regarding the influence of uncertainties, and test the effectiveness and robustness of policies given these uncertainties (Pruyt, 2010).

I will use the open-source Exploratory Modelling and Analysis EMA workbench for Python (Kwakkel, 2017, p. 201) to identify behavioral patterns and test and evaluate policies to find robust policies (Kwakkel, 2017). The SD model consists of several structural and parametric uncertainties and multiple variable values, which I must test in the analysis. EMA workbench has a special connection built to run experiments with Vensim (Ventena Systems, 2023) efficiently.

This study will focus on scenario discovery and analyzing scenarios of interest to scope the research to a suitable level. During this phase, I will explore scenarios that meet United Nations' global climate change and food security targets. Scenario discovery uses algorithms such as the PRIM algorithm (Friedman & Fisher, 1999), classification and regression trees (Breiman & Ihaka, 1984), and time series clustering approaches (Kwakkel et al., 2013; Steinmann, 2018). In this research, I will use the PRIM algorithm.

The PRIM algorithm is a handy tool for scenario discovery in this context, as it identifies regions in the input space where the model's output exhibits specific desired characteristics. PRIM is an iterative, data-driven method that seeks to identify ‘boxes’ in the multidimensional input space containing a high concentration of cases that meet specific criteria. These boxes are a subset of scenarios where particular outcomes or vulnerabilities are more likely to occur (Friedman & Fisher, 1999). The algorithm's strength lies in its ability to efficiently deal with large datasets and high-dimensional input spaces while maintaining interpretability and ease of use.

By employing the PRIM algorithm in conjunction with EMA and the SD model, I can effectively explore the influence of uncertainties on the system and identify robust policies that can lead to achieving global targets. I will perform 10,000 scenario runs and analyze these using the PRIM algorithm. With the algorithm, I will narrow the uncertainty space to scenarios with desirable outcomes. The narrowed-down uncertainty space is input for the country-specific runs that contain more detail. Because of the sheer amount of data each run will provide, I will limit these runs to 200.

In summary, the Exploratory Modeling Approach (EMA) and its application using EMA workbench, combined with the PRIM algorithm for scenario discovery, offer a suitable method for dealing with deep uncertainties in the LULUCF, food, and carbon system. By identifying behavioral patterns, testing policy robustness in the presence of uncertainties, and using the PRIM algorithm to discover scenarios of interest, EMA will help inform decision-making and contribute to the identification of effective policies for achieving global targets.

3 Model

I developed an SD model to represent the real-world system. This chapter discussed the model structure, several sub-systems, and data input, including policy levers, uncertainties, and generic input data. Afterward, I discuss the validation of the model. The models, datasets, and scripts used can be found in my Github repository https://github.com/GvanSmeden/EPA_Thesis.

3.1. System Dynamics model

3.1.1. High-level overview of the system dynamics model

Vensim (Ventena Systems, 2023) is used to build the model. Vensim is a widely-used software for SD modeling, providing a comprehensive suite of tools for simulating complex, nonlinear systems. This study's selected time horizon is between 2011 and 2100. 2011 is the start year of the model since most countries have available data for this year, and the food model from Auping (2018) is based on 2011 data. The model runs up to 2100 since most data sources, such as the World Bank, provide projections until that date. These data sources are essential as external drivers in the model. The time horizon up to 2100 allows an understanding of the long-term effects of land cover change, food demand, supply, and the global carbon cycle. Nonetheless, the system also has a built-in delay of 200 years. Therefore, some dynamics are underrepresented within this period.

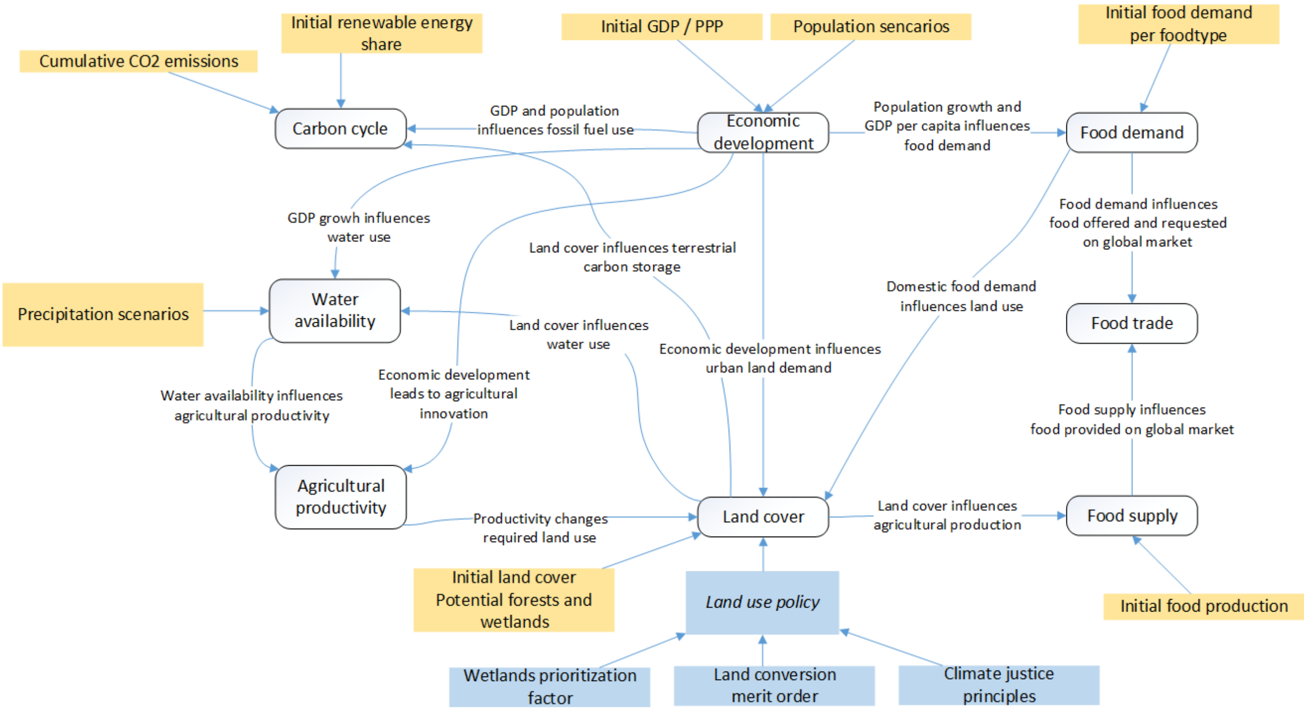


Figure 2 – Sub-system diagram – *sub-systems are shown in rounded rectangles, policies in blue, external input in yellow, and relations in the text on arrows.*

Figure 2 displays a subsystem diagram that represents the system and its sub-models. The complete system consists of eight subsystems: water availability, agricultural productivity, land cover, food supply, food trade, food demand, economic development, and the carbon cycle. The sub-models economic development, agricultural productivity, land use, food supply, and food demand will be calculated for each country using subscripting. The land cover, carbon cycle, and food trade system will aggregate national output globally to display dynamics worldwide.

The water availability, agricultural productivity, land cover, food supply, and food demand sub-models are based on the model from Auping (2018), where they developed food consumption and food supply nationally. The global carbon cycle is derived from a model by Willem Auping based on the IPCC report '*The Carbon Cycle and Atmospheric Carbon Dioxide*' (2018). These different models are adjusted to make them fit for purpose, adjusted to calculate for each country simultaneously, expanded by the food-trade and economic development sub-model, and connected to display the feedback loop between the carbon cycle and the food system.

Water availability takes as input weather scenarios per country and GDP into account and feeds into the water availability into the agricultural productivity sub-model. The agricultural productivity will take water availability and economic development as inputs and calculate the agricultural productivity of a country. The land cover sub-model will represent the land cover of each country. The land cover will be determined by the required land for food production (based on food demand and agricultural productivity), urban land demand (based on population growth), and terrestrial carbon storage (based on terrestrial carbon storage policy). The land conversion merit order prioritizes specific land cover types for agriculture, terrestrial carbon storage, or no clear preference. A country's initial food production will determine the distribution of food production on agricultural land. The agricultural land cover and productivity determine how much food a country produces. Population size, national dietary preferences, and adjusted for GDP growth Food demand is determined by. A country's excess food will enter the global food trade market, where other countries can buy it if needed. The carbon cycle will calculate the total carbon stored in the terrestrial system by land cover, the ocean, and fossil fuel use based on GDP and renewable growth, and the difference will determine atmospheric carbon change.

3.1.2 Sub-systems

I will shortly discuss the most relevant sub-models for this analysis: economic activities, food trade, land cover, and the global carbon cycle.

The economic activities and food trade are simple sub-models. Economic activities include population growth scenarios, initial GDP, GDP growth, and renewable energy share. Initial GDP is either real GDP or purchasing power parity. GDP growth is adjusted for the population scenario and grows more if the population grows more. Lastly, the renewable energy share is determined by the initial renewable energy share, multiplied by the average renewable growth, and normalized by the renewable energy growth potential.

The food trade sub-model represents trade between countries. It inputs the food demand and production per country and calculates the net food balance. If a country has an oversupply of food, this will enter the global food supply. If a country has a food shortage, it will request this food type in the global food market. The available food from the global food supply is distributed between the requesting countries using the allocate available algorithm. Countries are prioritized based on their GDP per capita since a higher GDP per capita will give them more money to pay for food in the global market.

The land cover sub-system simulates a country's land cover over time, distinguishing between forest areas, wetlands, permanent meadows and pastures, arable land, permanent crops, urban area, and other land. These categories align with OECD land use data (2021), simplified to focus on terrestrial carbon storage, agriculture, and urban land. To simplify, I aggregated all non-productive land covers as 'other land'. The land cover composition may change if food demand patterns necessitate different agricultural land cover ratios.

Annually, a set percentage of national land can be converted into the ideal land composition using the allocate available algorithm, with land priorities tested as policy input. When a country still has the potential to expand wetlands and forestland and has an unmet national terrestrial carbon storage target, this forms the additional land needed for terrestrial carbon storage. The global carbon storage target is distributed among countries using the terrestrial carbon storage burden distributor that uses the allocate available algorithm, considering climate justice principles that prioritize countries differently in distribution.

Demand for additional agricultural land relies on domestic food demand, potentially causing a yield gap. Current urban land, linearly increased with population growth, forms the urban land demand. By integrating these elements, a cohesive land-use system is developed to analyze the impacts of land-use policies, terrestrial carbon storage, and population growth on land-use patterns and distribution.

The global carbon cycle sub-system is essential to this study as it quantifies the carbon sequestration potential of various land use policies and land cover types. The carbon cycle sub-system consists of several stocks and flows that calculate the carbon stored in the atmosphere, terrestrial systems, ocean, and fossil fuels, as shown in Figure 3. It considers carbon emissions from land-use change, such as deforestation, and carbon sequestration through afforestation, reforestation, and wetland restoration. Additionally, the sub-system considers anthropogenic carbon emissions from fossil fuel combustion determined by the average carbon content of the GWP (IPCC, 2018) and normalized by the renewable energy share.

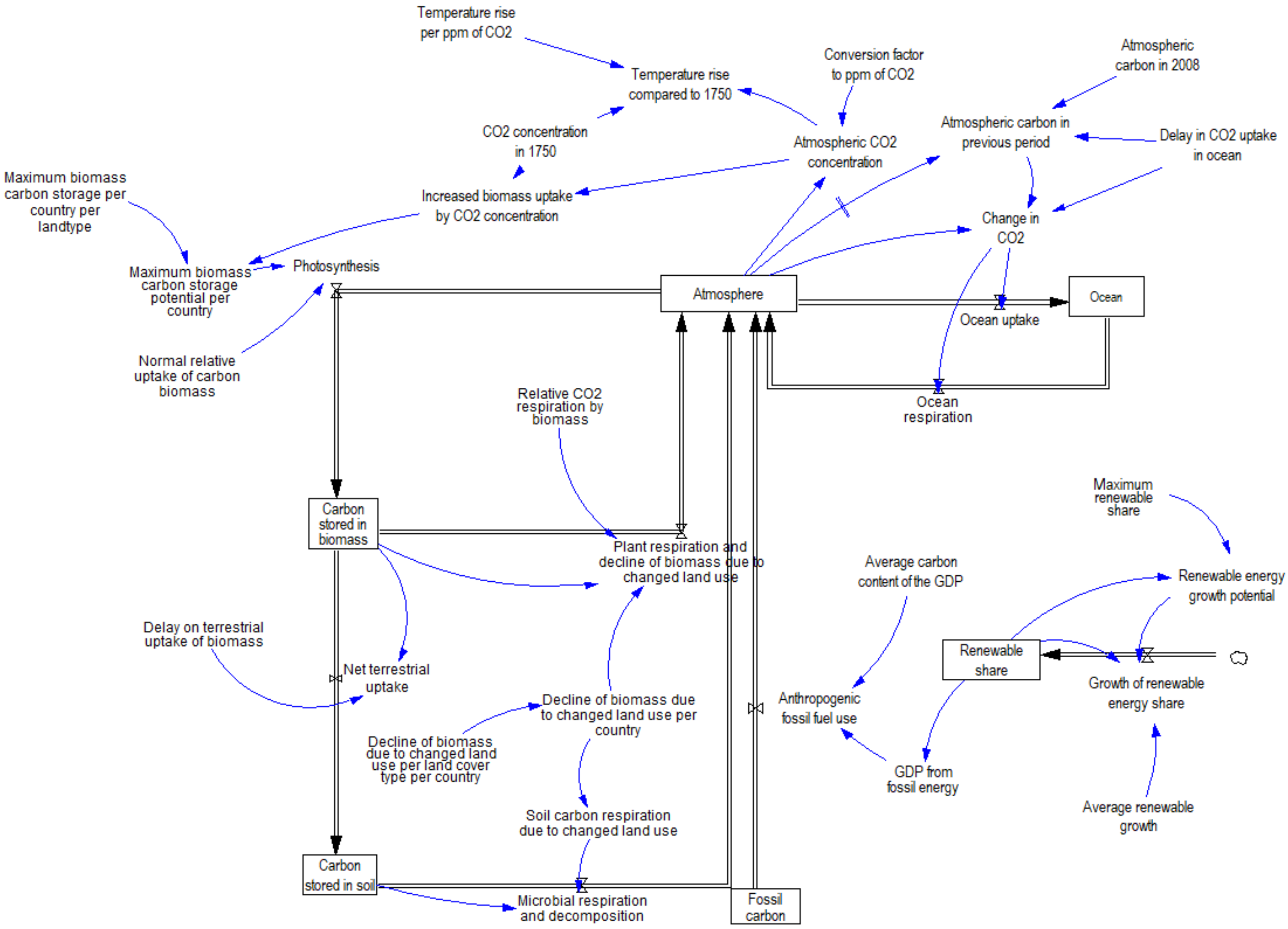


Figure 3 - Stock-flow diagram of the global carbon cycle – *rectangular boxes represent stocks, double-lined arrows represent flows, and relations are represented by blue arrows.*

The carbon cycle sub-system calculates the total carbon stored in the atmosphere by adding fossil fuel emissions, plant and soil respiration, and ocean respiration and subtracting photosynthesis and ocean uptake. The oceanic carbon uptake is calculated based on the standard atmosphere-ocean transfer stated by the IPCC (2018) and an additional relative oceanic uptake based on changes in atmospheric carbon. The relative oceanic uptake means that increasing atmospheric CO2 leads to more oceanic uptake, but when atmospheric CO2 reduces, extra CO2 from the ocean will respire. The terrestrial carbon sequestration is determined by the land cover and land use changes, with forests and wetlands playing a crucial role in storing carbon. Carbon sequestration rates are based on the values stated in (IPCC, 2018) and capped by the maximum biomass storage capacity, defined by the current biomass storage per land cover type divided by the total land surface.

3.2. Input data

Some of the data inputs from Auping (2018) could be incorporated into the model of this research. Still, additional data had to be collected and processed to tailor the model for specific purposes and extended projections until 2100. The data collection consisted of collecting and processing some global and some country-specific datasets.

First, I gathered data for each country specifically. As not all data was available in the desired structure, several techniques had to be used to collect and process the data to suit the import structure of Vensim. Table 1 shows the additional data that has been added and the sources that have been used to obtain them. These will be elaborated on further below.

Table 1 - Input variables and sources

Variable	Source
Precipitation scenarios	(World Bank, 2023a)
Population scenarios	(United Nations, 2023)
Share of global carbon emissions	(Our World in Data, 2023)
Land cover composition	(OECD, 2021)
Potential forests and wetlands	(FAOSTAT, 2017; OECD, 2021)
Renewable energy share	(World Bank, 2023b)
Agricultural share of GDP	(World Bank, 2023b)
Carbon storage potential per land cover type	(German Advisory Council et al., 1998)

Precipitation scenarios were collected from the Climate Change Knowledge Portal from the World Bank (World Bank, 2023a), which contains country-specific data per country. It is possible to download time series data to assess the implications of numerous factors on food demand, land use changes, and carbon dynamics. The country-specific data included precipitation based on CMIP5 and scenarios based on RCP2.6, RCP6.0, and RCP8.5. With the recurring URL link, I downloaded the 519 data files efficiently. I developed a small tool to load these files and structure them accordingly for input for the Vensim model.

Population data has been obtained from the population prospects for 2022 (United Nations, 2023). For 2011 – 2021, it was possible to use actual data; therefore, there was no deviation between the different growth-scenarios for this period. This dataset had pre-defined population growth projections categorized as '*Low variant*,' '*Medium variant*,' and '*High variant*.' The data only had to be transposed and adjusted to fit the required data input structure for the Vensim model.

A share of global carbon emissions was obtained from (Our World in Data, 2023). They provided a complete overview of cumulative historical carbon emissions, including land-based emissions. The data then only had to be filtered for 2011 values and restructured to match the input dataset.

Land cover composition per country comes from (OECD, 2021) and represents data from 2015, as the closest other dataset is from 2004. Since this data has only been used to calculate urban area, forest land, and wetlands, the impact on the model is assumed to be negligible. The dataset provided could then be processed to create the initial forestland, wetland, and urban land columns. Values for the composition of agricultural land come from (FAOSTAT, 2017). Since this dataset is tailored for agriculture, it is assumed that this dataset is the most accurate. Other land has been calculated by total land and subtracting all land cover types defined earlier from it. The potential forestland is determined by adding up the land cover from tree cover, grassland, wetland, and cropland, assuming that these land cover types could become forestland. For potential wetlands, the maximum value is taken between the 1992 and 2015 datasets for wetlands. No clear literature states which land cover types can be converted to wetlands for terrestrial carbon storage, but only ones describing what it converts to.

Renewable energy share and agricultural share of GDP were obtained from World Bank Open Data (World Bank, 2023b). The data was structured like the input data for Vensim; therefore, only the column for 2011 had to be selected and matched with the existing data file based on ISO3-codes of the countries.

Lastly, global data had to be included for model expansion. For this, I aimed to have data at an aggregated level that would contain a carbon storage potential per surface unit that would be representative compared to the global average for this land cover type. Several sources describe terrestrial carbon storage divided by country, per storage location (biomass or soil), or at a much more detailed level for sub-categories of land covers. Therefore we took the data from (German Advisory Council et al., 1998) and divided this value by the total share of each land cover type to determine the storage capacity per km2. This value contains much uncertainty and will be included in the uncertainty analysis.

3.3. Validation

Model validation was carried out consistently throughout the model development process. Several validation tests defined by (Forrester & Senge, 1980) were used to evaluate if the model was fit for purpose. The overarching purpose of the modeling process is to understand how different land cover policies impact the global food and carbon systems. Through this process, I aim to assess the viability of terrestrial carbon storage strategies and their implications. As a model is a simplified representation of the real-world, this has implications to the extent that specific arguments can be made based on the findings. Below are the most relevant model limitations, and implications for the validity of results will be discussed, followed by an evaluation of whether or not the model is fit-for-purpose.

3.3.1. Model limitations

Regarding the climate system, several aspects are represented very simplified or completely omitted. Only the global carbon cycle and a limited endogenous water availability model have been included in regards to the climate system, and some feedback loops have been excluded. More specifically, in the global carbon cycle, land cover-specific carbon flows are missing, only seven land-cover categories are included, climate-based land cover change is not included, and no greenhouse gases other than carbon are integrated. Consequently, I can not definitively quantify the contribution of terrestrial carbon storage to climate change mitigation or accurately project the expected temperature change that will happen if specific policies are included. Also, the land that can be converted to forests and wetlands is based on simple estimations of the current land cover; in reality, it is much more complex and could be overestimated or underestimated in the model. The model is partially constructed to get a better understanding of the system and its dynamics. Therefore it is less relevant to quantify the values reliably. By also integrating the input variables and uncertainties, we can explore the system's sensitivity to these data points and determine if it is problematic.

In the experimental setup, I will not include all uncertainties from the system since this will make the dataset too extended and take too long to do iterative experiments. For example, no uncertainties related to country-specific adherence to global policy or country-specific perspectives on climate justice were included in the policies. Additionally, only five different climate justice principles and interpretations were included. No literature clearly stated how climate justice principles should be translated to terrestrial carbon storage policy, meaning this is a normative uncertainty. Because of this, I won't be able to predict how these different climate justice principles and perspectives might translate to real-world behavior or determine the robustness of my findings. Nonetheless, it allows me to prove the principle of finding non-discriminatory policies; it can first indicate the implications these climate justice principles could have on terrestrial carbon storage burden distribution.

From a socio-economic perspective, the model is developed to explore the implications of land cover policies on socio-economic factors such as food security and economic growth, including the dilemma between these factors. However, the representation of the food trade system was simplistic and lacked feedback loops in food demand. There is also no connection in the model between agricultural production and GDP, and it does not account for other profits and costs associated with land cover change, such as wood sales. As such, I could not reliably predict food shortages after trade adjustments, determine their severity, or explore the policy's consequences on a country's economic development. Considering these limitations, I used GDP per capita as an alternative indicator for food shortage after trade as one of the distributors representing the ability-to-pay. The goal of this research is not to show trade-offs; therefore, it is acceptable that the reliability of socio-economic KPIs is insufficient.

Since the model has many exogenous drives, the model can only be used for the period that reliable predictive data is available. Thus, I could not explore dynamics beyond the 2100 time horizon. This limits the ability for intergenerational justice comparison and explores some effects from dynamics that have long delays, but intergenerational justice was already kept outside of the scope of this research. The scope of the research also focuses on the period up to 2100 because substantial system changes have to occur within this timeframe to avoid the risk of disastrous irreversible effects.

The limitations above necessitate careful interpretation of the model's results. Despite these constraints, the model provides valuable insights into the potential of terrestrial carbon storage strategies and the influence of different land cover policies. It also allows for comparing the results of climate justice principles and therefore determining their importance to be included as uncertainties in future research.

3.3.2. Validation tests

First, the most relevant tests from Forrester & Senge (1980) are discussed in detail. Additional tests are shown in Table 2 and discussed in less detail.

Boundary adequacy

This exploratory research demonstrates the dynamics between the food system and the global carbon cycle. Our most important outcomes of interest are; food shortage and temperature increase compared to 1750. For modeling the temperature increase, the model contains the most sizeable carbon stocks and flows and therefore is adequate. Our model is overly simplified for food shortage and lacks multiple feedback loops that could lead to different behavior.

The food trade system does not contain stocks, allows trading on a global scale for all food types, and does not contain pricing. Integrating trade regions and stocks specifically for each food type to understand better food trading between countries would make it more realistic, display the global economy's limitations, and even help define political leverage points. The lack of pricing is limiting the insights that can be obtained regarding the share of agricultural productivity in a country’s GDP. It is making it impossible to implement countries focussing on profitable crops and to evaluate if trade dynamics are represented realistically.

Potential land that can be converted to wetlands, forestlands, and agricultural land is not adjusted for climate-based land cover change. This simplification leads to the underrepresentation of tipping points and shows how some countries might be more affected by climate change. Therefore we can only explore the temperature change and not the impacts of these changes.

Behaviour-anomaly

The behavior anomaly test has been a continuous process during the modeling cycle. Unexpected and unrealistic behavior was shown that was traced down to improve the model. Some of the variables that were mostly observed to detect anomalies were; temperature increase, total land surface, total land demand, national required addition terrestrial carbon storage since 2011, global food supply, net food balance, and net carbon emissions. Since subscripting was used, multiple countries were explored, often composed by a set of known countries to the modelers, such as the USA, the Netherlands, India, China, and Kenya. For country-specific values, it was easy to compare if they made sense. Global variables were also possible to predict. While looking at behavior anomalies, many model-improvements were achieved.

Surprise-behavior

Predictions were made on behavior and relations between variables during the KDE plots and PRIM analysis. Some behavior and relations were predicted, but some did not show what was expected, and the model showed more uncertainty than others. For example, initially, it was not expected that limiting land conversion would be a way to minimize temperature increase and food shortage. After looking into the relations, we understood the system better and developed new insights into the system. The main lesson that was obtained was the delay in productivity after the land cover change, in which there was no carbon storage in biomass and no agricultural productivity. It taught me the importance of international collaboration and a long-term strategic approach when dealing with land cover policy.

Table 2 - Validation tests

Validation type	Validation test	Short argumentation
Structural	Structure verification test	Use of scientific sources
	Parameter-verification tests	Comparing temperature with real-world projections
	Extreme-Conditions tests	Implicit to robust decision-making
	Dimensional consistency	Built-in tool in Vensim
	Boundary-adequacy tests	It contains relations for proof of concept purposes.
Behavioural	Symptom generation	The model generated otherwise hard-to-understand behavior, such as global warming, and which factors led to this (e.g., terrestrial carbon emissions, fossil fuel emissions, and interaction with the ocean).
	Multiple mode	The model demonstrated different behavior patterns when testing climate justice principles.
	Behavior characteristic	Reversed effect of the ocean was observed.
	Behavior-prediction	The system showed the global warming effect within the boundaries of IPCC predictions.
	Pattern prediction	Stabilizing behavior in temperature increase was observed because negative feedback loops were not included.
	Family-Member test	The model successfully ran for 173 countries.
	Behaviour-anomaly	Flaws in the model were found by testing different options. Several model iterations were performed based on strange results such as extremely high-temperature increase, food supply not distributed as expected, and land covers not converted as desired.
	Surprise-behavior	Unexpected results and the dynamics behind them were investigated, making sense of some behavior by tracking the relations and feedback loops. An example is the impact of the land conversion rate on food shortage and temperature increase.
	Extreme policy	Implemented in experimental design with terrestrial carbon storage target ranging from 0 GtC to 1000 GtC.
	Behavior sensitivity	Terrestrial carbon storage is less needed, with a high renewable share and low GDP growth.
	Changed behavior test	Plausible impacts of policy interventions were demonstrated.
	Policy sensitivity	I observed substantial sensitivity in the model to land conversion merit order.

3.3.3. Qualitative system exploration

I use the kernel density estimate (KDE) plots to explore the sensitivity of the factors of interest to specific parameters to validate if our analysis has reasonable outcomes. I selected the output variables global food shortage and global temperature increase since this research strives to optimize for these factors worldwide. Additionally, I use the KDE plot to compare the outputs of 2 experiment datasets, both 10.000 runs, to validate if the scenario sampling size was sufficiently broad. If there is little to no variety between the factors, we can assume that our sample is big enough. In Figures 4 and 5, there is barely any variety to be observed for both the impact on temperature rise and food availability. These are the two output factors we are trying to optimize, and therefore, we can agree that the dataset is fit for purpose and the amount of runs in the experimental set is sufficient.

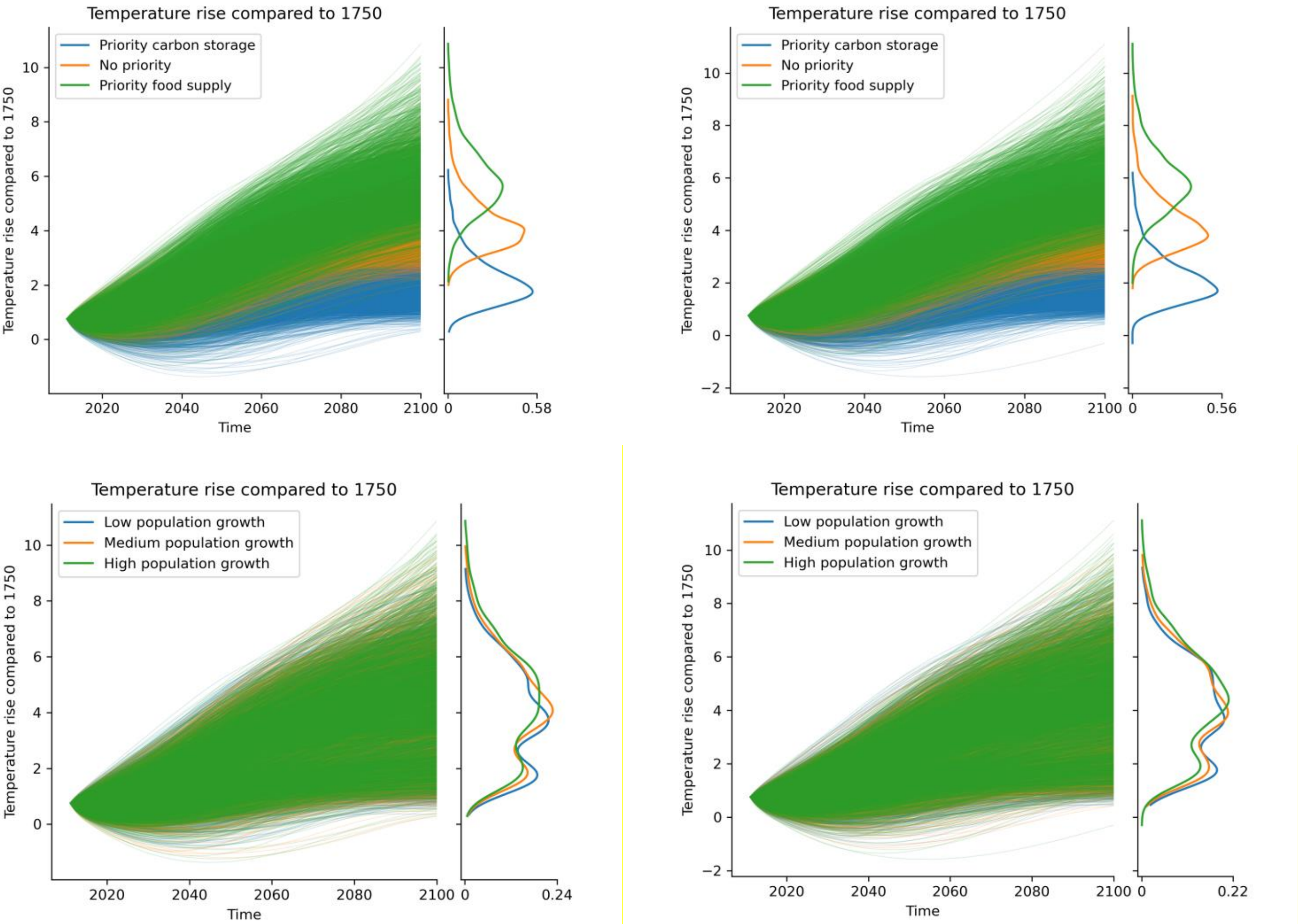


Figure 4 - KDE plots 2x 10.000 experiments – *Temperature rise clustered for land conversion merit order and population growth*

The plots in Figure 4 on temperature increase since 1750 show the final temperature increase in 2100 range from a potential decrease of temperature since 2011 up to an increase of approximately 8 degrees. As we are experimenting with extreme scenarios of extreme renewable growth (1 - 10%), extreme terrestrial carbon storage targets (0 - 1000GtC), and a high range in global population (6.8 billion – 14.4 billion), it makes sense that the outcomes will be on the edges of reality. The more frequent occurring cases range from 1-5 degrees which are sensible compared to IPCC scenarios.

The hypothesis for the plot displaying temperature increase categorized by climate justice principles would be that it would show a substantial difference between these categories. The graph shows three differentiated peaks that also fit according to the priorities of the land conversion merit order. The hypothesis for the plot displaying temperature increase categorized by population growth was expected to show a substantial sensitivity between the different population growth scenarios because population growth is connected to GDP growth. Since the GDP is coupled with fossil fuel emissions and the growth is compounding in the model, one would expect that differences will become substantial. Additionally, a higher population would require more food production, limiting land cover available for terrestrial carbon storage. Lastly, population growth would require more urban land even though urban. Nonetheless, only a marginal difference is observed.

While analyzing the relations leading up to this, we better understood the system. Multiple dampening effects in the system can clarify the limited sensitivity of temperature increase to population growth, renewable energy share (especially in higher cases, this will dampen the effect), of GDP growth in the long term. In contrast, population scenarios remain constant in 2011 – 2021 since this is based on real-world data. Additionally, the increased need for agricultural land is limited because the intensity of agriculture will increase. This also shows a limitation of the model since countries could also increase their agricultural intensity based on export potential, which is now excluded from the model. Another dampening effect on food requirements is that countries will have less food waste once their GDP increases. Also, dietary patterns adjust when GDP increases, where further developed economies will reduce their meat consumption and therefore require less land to meet their food demand. Urban land demand will only range from 2.2% – 3.6% of total land between the population scenarios. Therefore, these differences are minimal. Also, not all increased food shortage will be covered, hence the increase in food shortage represented in Figure 5. Lastly, the global carbon system will also function as a carbon sink, where increased atmospheric carbon leads to higher oceanic and terrestrial uptake.

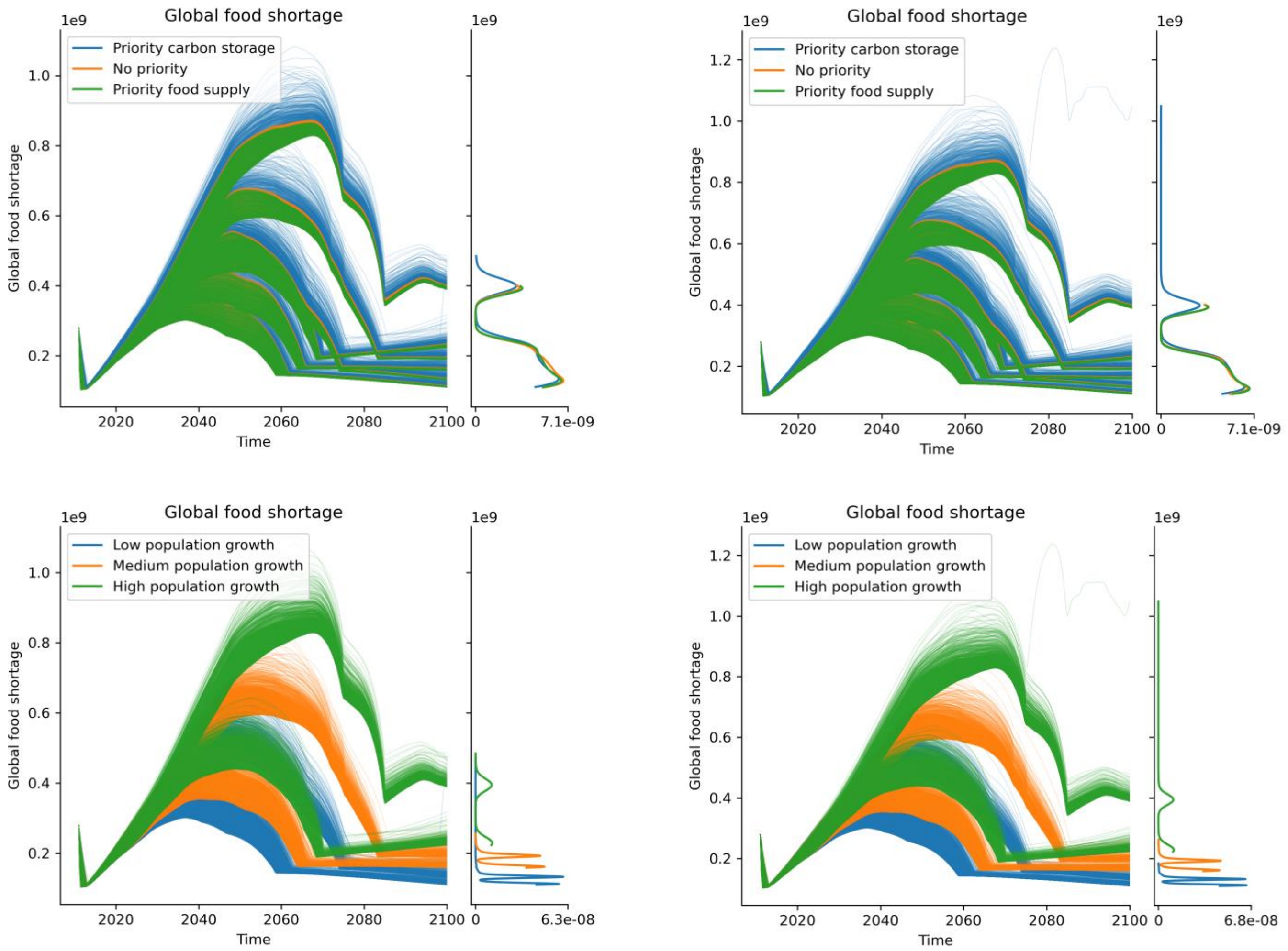


Figure 5 - KDE plots 2x 10.000 experiments - *Global food shortage clustered for population growth.*

The plots in Figure 5 show the global food shortage ranges from relative stabilization to a substantial increase in food shortage. Still, the range remains within factor 5 of the current situation and could be clarified by the built-in system where countries optimize to minimize domestic food shortage. This way, some food types will be oversupplied in the global food market, and others will have more of a deficit. Additionally, economic development will influence dietary preferences, requiring agricultural land cover adjustments. As populations in low- and middle-income countries will contain most if not all population growth and have high GDP growth, this impact on food shortage will be substantial. Note that the model defines food shortage as not being able to meet projected dietary preferences, which would not mean that there is a nutritional food shortage. Therefore, the possible outcomes fall within a realistic range of results, and we can continue.

An interesting observation about the structure of the plot is that there are two clear lines per population scenario. This represents the difference in GDP scenarios, which makes sense since it influences dietary patterns. Figure 6 shows the KDE plot categorizing GDP scenarios to distinguish clearly. When further looking into these patterns, you would initially project that it will be a divergent pattern since compound GDP growth exists. Instead, there is a crossing of both lines where the actual GDP scenario sometimes experiences less food shortage. Two factors in the model can explain this; food waste and dietary patterns, where the demand for animal-based products will reduce again after reaching a specific level. A limitation of the model is that the GDP growth factor is externally driven and only adjusted to population growth. As agricultural productivity is increased by GDP growth, there is no difference in agricultural productivity between the GDP / purchasing power parity scenarios.

In terms of the relations between land conversion merit order and global food shortage, there was expected to be a substantial difference in outcomes since terrestrial carbon storage would go at the cost of agricultural land and vice versa. There are only minor differences to observe. This can be explained by the tendency of the system to intensify agriculture if a food shortage appears. The system then attempts to go increase agricultural land to normalize this, but no mechanic will enforce it if no land is available, and therefore high agricultural intensity will remain.

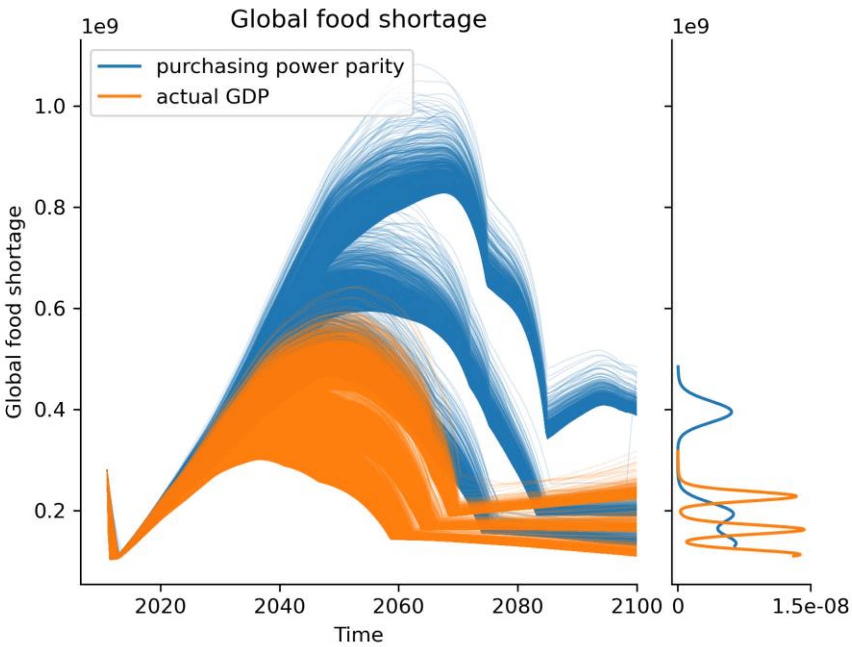


Figure 6 - KDE plot global food shortage categorized by actual GDP / purchasing power parity.

3.4. Experimental setup

Experimental design

It is crucial to focus on the uncertainties that exert the most significant influence on these outcomes to develop robust and comprehensive insights into the dynamics of food supply and terrestrial carbon storage, i. By identifying and analyzing these key uncertainties, I can better understand the potential outcomes of the system. In the experimental setup, Latin Hypercube Sampling for scenario selection is used, a built-in function in the EMA workbench, ensuring efficient sampling and reducing sampling bias. Table 3 presents a detailed overview of the factors and their corresponding ranges.

Table 3 - Uncertainties

Variable name	Explanation	Unit	Min	Max	Reference
Switch population scenarios	Varying population scenarios in the categoryies low, medium and high.	Dmnl	1, 2, 3		(United Nations, 2023)
Switch GDP to purchasing power	Switch between nominal GDP and Purchasing Power Parity. Purchasing Power Parity will give higher values with relative higher purchasing power.	Dmnl	1, 2		(Auping et al., 2018)
Average renewable growth	The growth factor of the renewable energy share. This factor represents the fraction of the potential renewable growth that is achieved in a year.	1/Year	0.05	0.1	Assumption
Switch annual precipitation scenarios	This switch goes between 3 rainfall scenarios of a country. The scenarios represent low, middle and high.	Dmnl	1, 2, 3		(World Bank, 2023a)
Delay on changes in annual plant production	This defines the time that it takes to adjust the composition of annual plants within a country.	Year	3	10	(Auping et al., 2018)
Delay on changes in permanent crops production	This defines the time that it takes to adjust the composition of permanent crops within a country.	Year	5	15	(Auping et al., 2018)
Land fraction available for conversion per year	Each year a factor of the existing land will be readjusted to fit to the ideal composition. The fraction determines this value.	1/Year	0.01	0.1	Assumption

Delay on carbon respiration due to changed land use	After the land cover has changed, the carbon that is in the soil will gradually respire and go to the atmosphere. The delay represents the duration that it takes for the carbon stored in soil is fully respired.	Year	150	250	Broad bandwidth around (IPCC, 2018)
Initial relative carbon respiration by changed land use	This is an initial value about the state of carbon respiration, since there is a long delay.	1/Year	0.0005	0.007	Broad bandwidth around (IPCC, 2018)
Normal lifespan of soil carbon	Factor defining how long carbon in general stays in the soil before it is renewed.	Year	30	48	Broad bandwidth around (IPCC, 2018)
Relative CO2 respiration by biomass	What part of the biomass is emitted to the atmosphere in the normal situation.	1/Year	0.09	0.13	Broad bandwidth around (IPCC, 2018)
Delay on terrestrial uptake of biomass	The duration for carbon in biomass to be taken upby the soil.	Year	4.6	18.4	Broad bandwidth around (IPCC, 2018)
Relative additional oceanic CO2 exchange	On top of the continuous transfer between atmosphere and the soil, additional uptake or emissions happen. This is based on the change in atmospheric concentration.	Dmnl	0.3	0.5	Broad bandwidth around (IPCC, 2018)
Normal relative uptake of carbon biomass	Which fraction of the biomass capacity will be taken up each year by the biomass.	1/Year	0.17	0.28	Broad bandwidth around (IPCC, 2018)
Initial global biomass stored per landtype[Forest land cover]	Used to calculate the biomass carbon storage capacity simplified. Takes the global biomass storage in forests and divides that by total forest area.	GtC	400	500	Broad bandwidth around (German Advisory Council et al., 1998)
Initial global biomass stored per landtype[Other land cover]	Used to calculate the biomass carbon storage capacity simplified. Takes the global biomass storage in other land divides that by total other land.	GtC	20	100	Broad bandwidth around (German Advisory Council et al., 1998)

Initial global soil carbon stored per landtype[Wetlands cover]	Used to calculate the soil carbon storage capacity simplified. Takes the global soil storage in wetlands and divides that by total wetlands area.	GtC	300	550	Broad bandwidth around (German Advisory Council et al., 1998)
Initial global soil carbon stored per landtype[Forest land cover]	Used to calculate the soil carbon storage capacity simplified. Takes the global soil storage in forests and divides that by total forest area.	GtC	450	800	Broad bandwidth around (German Advisory Council et al., 1998)
Initial global soil carbon stored per landtype[Arabale land cover]	Used to calculate the soil carbon storage capacity simplified. Takes the global soil storage in arable land and divides that by total arable land area.	GtC	50	200	Broad bandwidth around (German Advisory Council et al., 1998)
Initial global soil carbon stored per landtype[Pastures and meadows cover]	Used to calculate the soil carbon storage capacity simplified. Takes the global soil storage in pastures and meadows and divides that by total pastures and meadows area.	GtC	125	500	Broad bandwidth around (German Advisory Council et al., 1998)
Initial global soil carbon stored per landtype[Other land cover]	Used to calculate the soil carbon storage capacity simplified. Takes the global soil storage in other land and divides that by total other land area.	GtC	25	200	Broad bandwidth around (German Advisory Council et al., 1998)

In this study, I also analyze a wide range of potential policies represented by levers. These are based on climate justice principles and terrestrial carbon storage potential. The aim is to explore their impacts on land use, food security, and carbon sequestration. These policy levers are displayed in Table 4. Examining these policy levers provides valuable insights into the trade-offs and synergies between terrestrial carbon storage and agricultural productivity while accounting for the climate justice principles underpinning different distribution forms.

Table 4 - Policy levers

Variable	Unit	Min	Max	Explanation
Land conversion merit order	dmnl	[1, 2, 3]		This policy lever determines the preference between developing new land for agriculture, developing terrestrial carbon storage land, or having no preference. Balancing land use for agricultural productivity and carbon storage is essential for addressing climate change and food security challenges. **1. Priority for terrestrial carbon storage** **2. No preference** **3. Priority for agricultural land**
Wetlands	dmnl	[0,1]		This factor assesses the prioritization of wetlands over

prioritization factor				forests for carbon sequestration. Wetlands store more carbon long-term in soil, while forests store more short-term in biomass. This distinction is crucial for evaluating the effectiveness of land use policies in mitigating climate change.
Initial global terrestrial carbon storage target	GtC	0	100	This policy lever sets the initial (short-term) target for global terrestrial carbon storage in gigatons of carbon (GtC). The target guides countries' land use decisions and helps evaluate the effectiveness of policies in achieving the desired carbon sequestration outcomes.
Final global terrestrial carbon storage target	GtC	0	1000	This policy lever sets the final target for global terrestrial carbon storage by the year 2100 in gigatons of carbon (GtC). The target guides countries' land use decisions and helps evaluate the effectiveness of policies in achieving the desired carbon sequestration outcomes.
Climate justice principle	Dmnl	[1,2,3,4,5]		This lever encompasses five different climate justice policies that distribute the global carbon storage burden among countries based on other principles: **1. You-broke-it-you-fix-it:** Allocates the burden based on each country's relative contribution to cumulative global CO2 emissions. **2. Efficiency prioritized:** Distributes the burden based on the relative levels of effective vegetal yield per square kilometer. **3. Ability to pay 1:** Considers each country's GDP per capita as an indicator of their ability to finance carbon sequestration efforts. **4. Ability to pay 2**: Focuses on each country's domestic food shortage, reflecting their ability to feed their population self-sufficiently. **5. Ability to pay 3:** Allocates the burden based on each country's ability to store terrestrial carbon, considering their land cover types and potential carbon storage capacity.

Each model run contains a lot of data for variables and timesteps. Therefore, only the global variables have been analyzed using PRIM. If also national data is included, this would add 173 entries per variable, making the dataset extremely large and slow to process. Using PRIM on the global variables that are the core focus for this research - global food shortage and temperature increase – scenarios of interest can be defined. Typically policy levers are not included in the prim sensitivity analysis, but in this case, policies have been included as uncertainties in our analysis. I included the policy levers as uncertainties because there is no global government, so national governments' implementation of global policies remains uncertain.

The PRIM algorithm helps to determine the subset of uncertainties (and policy levers) that will lead to the desired outcome. With the results of PRIM, the uncertainty ranges are reduced and used as input for a more extensive analysis run in which country-specific data is collected. Two hundred additional runs have been performed that contain this country-specific data that is used for the visualization and country-specific analysis.

4 Results

This chapter will discuss the results from the multiple modelling steps. I am starting with uncertainty analysis and then comparing the climate justice principles.

4.1. Uncertainty analysis

To find the scenarios of interest, I use the PRIM algorithm and categorization to find cases where the temperature since 1750 remains below 2 degrees, corresponding with the COP goals (UNFCCC, 2023). The PRIM algorithm will iteratively reduce the uncertainty space in multiple dimensions. It optimizes for maximum density, mass, and coverage. The trade-offs between coverage and density are explored using the show trade-off function, after which the suitable box can be inspected that is created with the peeling and pasting trajectory.

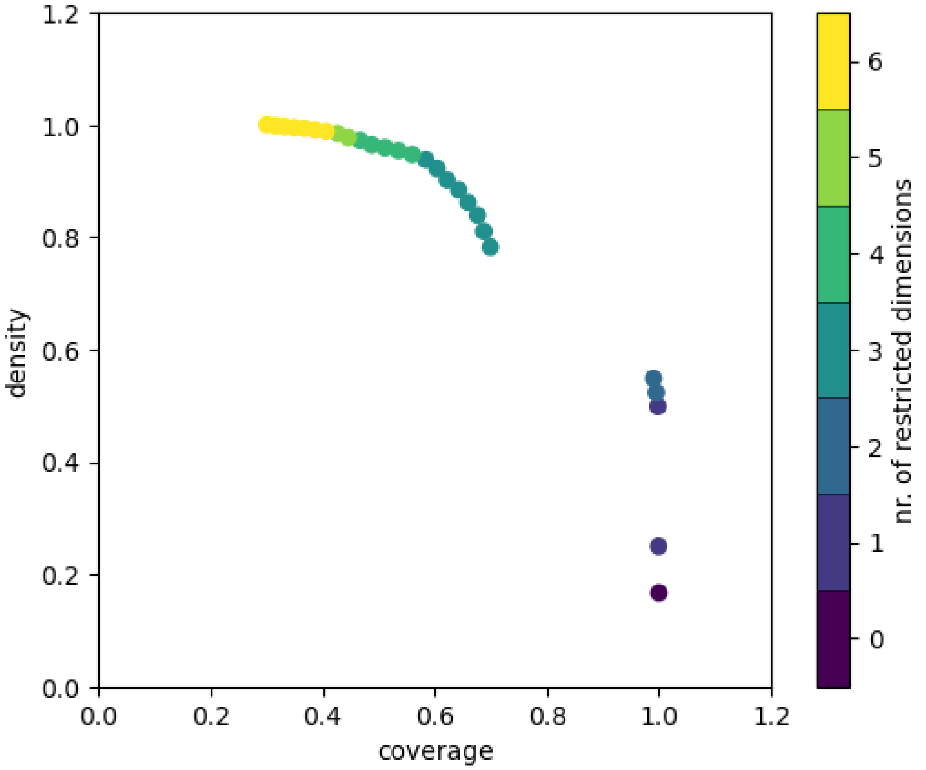


Figure 7 - Trade-off graph for temperature increase below 2 degrees

Figure 7 shows the trade-off graph between the coverage and density. By restricting three dimensions, almost complete coverage is achieved while maintaining a density of approximately 60%. The scenario space with restricted dimensions is called a PRIM box and is shown in Figure 8. On the left side, the uncertainties are shown, followed by the p-value and the range of the restricted dimensions. Based on the earlier insights on the system behavior, it would be expected to have the switch GDP to PPP, average renewable growth, land conversion merit order, and terrestrial carbon storage target as restricted uncertainties. The first three uncertainties are restricted, but the terrestrial carbon storage target is not. From this, we can deduce that there is no need to create more additional terrestrial carbon storage land. Still, it is essential that we at least conserve the existing high-carbon-containing terrestrial land.

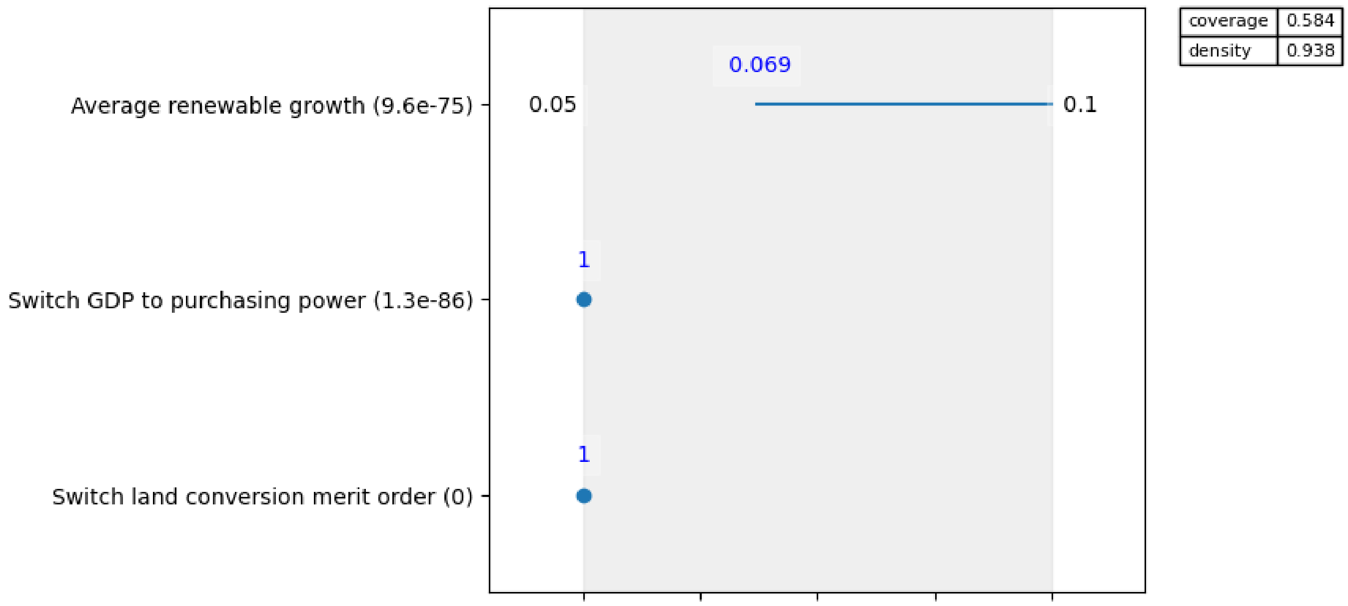


Figure 8 - PRIM box 12 temperature increase below 2 degrees

Our subsequent analysis is a similar PRIM algorithm but then on global food shortage. The ideal target function is that food shortage does completely eradicate, and there is no food shortage anywhere. In the validation part, it is already shown that global food shortage never reaches 0 or goes below 0. This is because of the model structure. Therefore we adjusted the target to a more realistic target, where food shortage reduces by 50% compared to 2011. As seen in the KDE plots, looking at the food shortage in the year 2100, a high food shortage in the period 2040 – 2075 is not considered in the analysis. Even in this case, only two iterations are needed, and one dimension had to be restricted to reach almost 100% density, as shown in Figure 9. When exploring stricter categorizations such as a quarter of initial food shortage, no cases passed anymore, therefore, I did not continue further narrowing down the goal function.

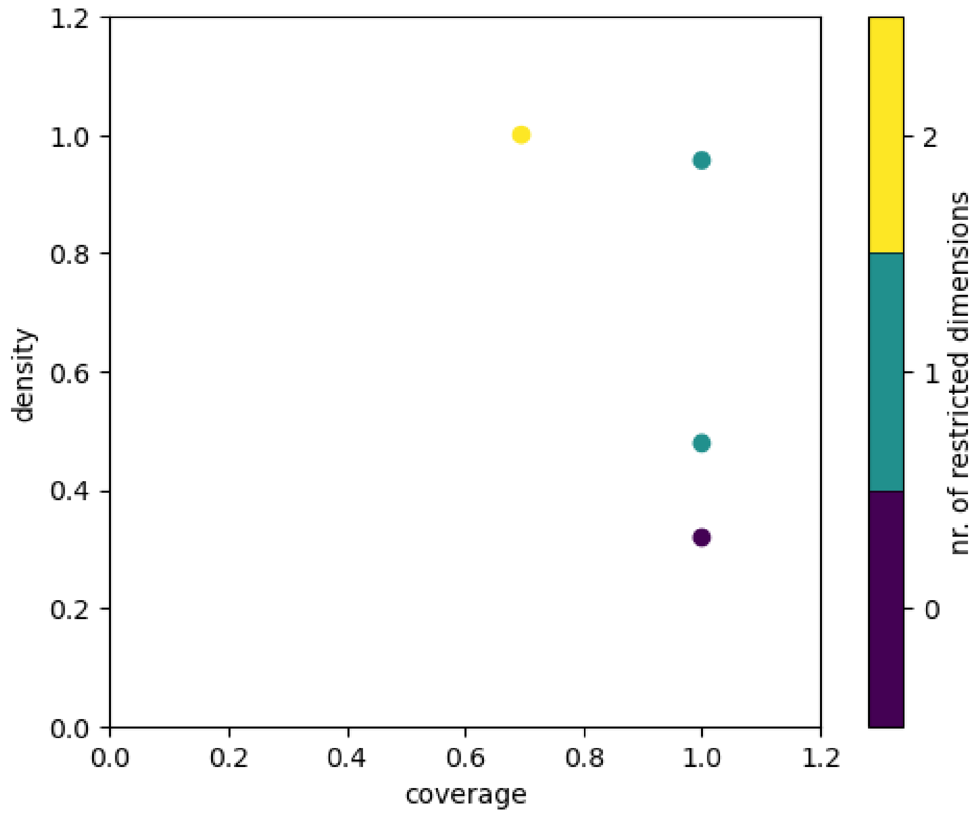


Figure 9 - Trade-off graph for global food shortage reduced by 50%

When exploring box two, population growth or a switch GDP to purchasing power was expected to be seen as the restricted dimensions. When looking at the prim box displayed in Figure 10, it is shown that population growth was the only predictor. Switch GDP to PPP was not. This can be explained by looking at the KDE plot in Figure 6. The food shortage converges between the two GDP scenarios, especially for the cases with low or medium population growth. Therefore, this will, in the year 2100, not be an effective way to divide the datasets.

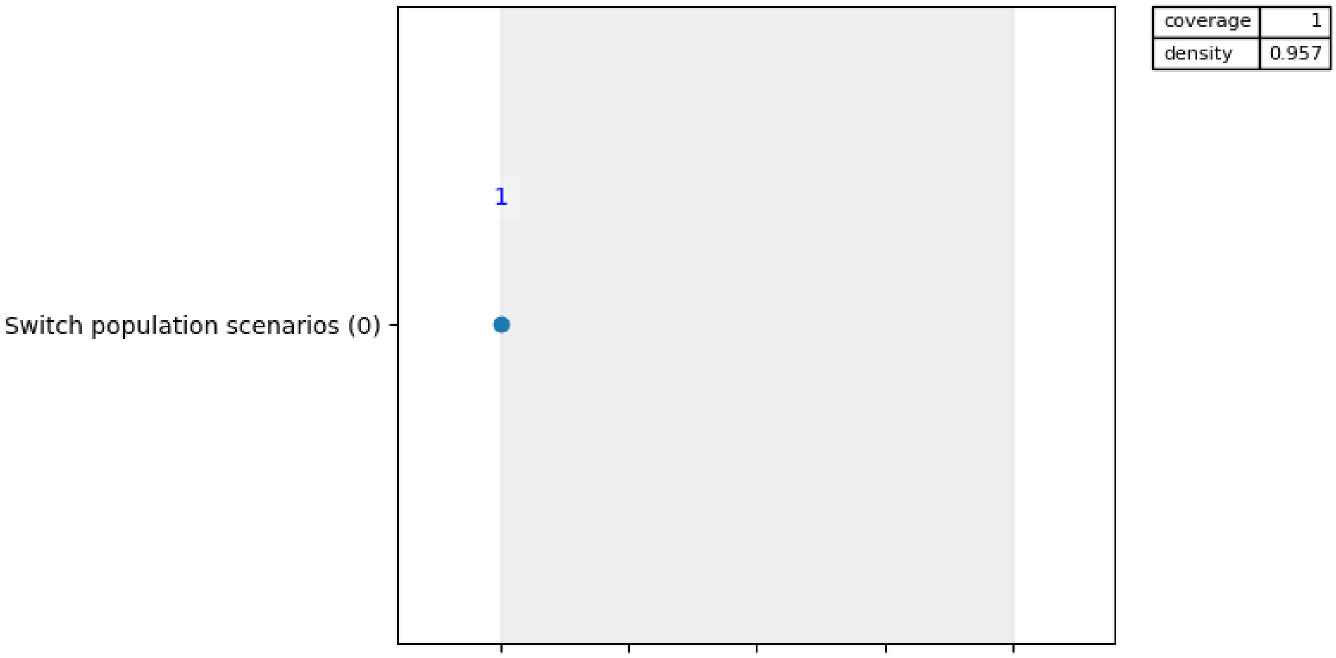


Figure 10 - PRIM box 2 global food shortage reducing by at least 50% compared to 2011.

The final PRIM analysis that has been performed is on the classification where both temperature is not increasing beyond 2 degrees and food shortage does not decrease to less than half of the initial value. In Figure 11 it is shown that more than 60% coverage with more than 70% density can be achieved by restricting 7 dimensions.

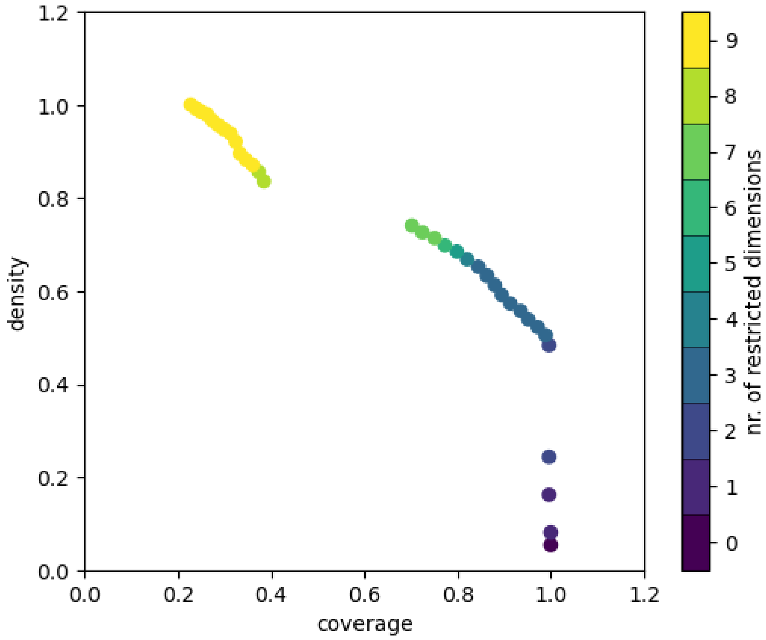


Figure 11 - Trade-off graph for global food shortage reduced by 50% and temperature increase below 2 degrees

When analysing box 20, displayed in Figure 12, I expected to see population growth, switch GDP to purchasing power, average renewable growth, land fraction available for conversion, and land conversion merit order. All these factors were present and no additional restrictions were significant.

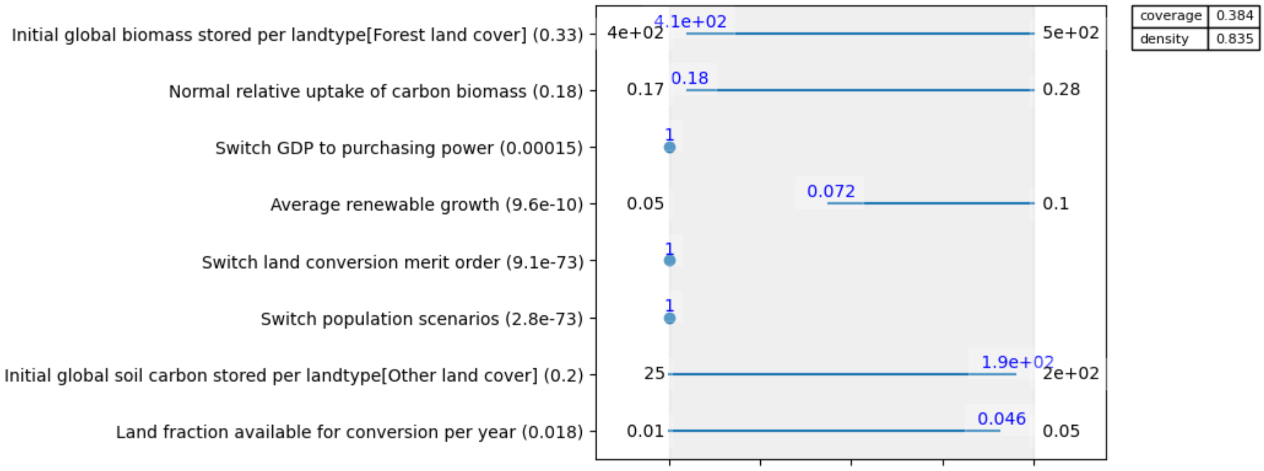


Figure 12 - PRIM box 20 for scenarios where both global food shortage does not increase compared to 2011, and temperature increase remains below 2 degrees

To conclude the uncertainty analysis, the main insights are on the uncertainty space and the policy levers. First, the system is sensitive to population scenarios, GDP, land conversion merit order, average renewable growth, and land fraction available for conversion, as could be expected based on the KDE plots. For this analysis, land conversion merit order is the most important effective policy lever I considered in this research. Additionally, average renewable growth is crucial in meeting the climate goals and keeping global temperature increase below 2, indicating that terrestrial carbon storage is part of a solution and not a complete solution to keep temperature increase below 2 degrees. Lastly, land fraction available for conversion could also be a seen policy lever. It shows that minimizing short-term land cover changes is essential since the terrestrial carbon and agricultural system will require long periods to reach their effectivity again. This would argue for reasonable certification procedures before the land cover can be adjusted. Population growth and GDP growth are factors that policymakers cannot easily influence but would require monitoring since their development highly influences how strict climate action has to happen.

4.3. Policy evaluation

The primary goal is to explore if it is possible to find a non-discriminatory terrestrial carbon storage policy, meaning land cover that must be converted for terrestrial carbon storage or existing forests and wetlands that must be conserved regardless of the climate justice principle being followed. As shown in Figure 13, there are barely any non-discriminatory policies where countries would be obliged to create additional terrestrial carbon storage land. According to the analysis, Saudi Arabia, Iceland, Argentina, Lesotho, Niger, and Kazakhstan will have to develop more terrestrial carbon storage capacity. Nonetheless, many more countries are shown where most existing terrestrial carbon storage land should be conserved, for example, Egypt, Yemen, Syria, and Afghanistan. This would imply that these countries do not necessarily need to develop more forests and wetlands but should at least keep the current ones present. Other countries can experience some freedom to operate until they reach the threshold of Japan, South Korea, Zambia, and Myanmar.

While interpreting the insights displayed in Figure 13, it is important to consider that efficiency-prioritization is introduced as a new climate justice principle. Traditionally it is not considered to be one of the climate justice principles. While in most climate justice principles, further developed economies would conventionally have to carry the most burden because they have a higher ability-to-pay and have contributed more to historical emissions, in efficiency-prioritized, they would not have to since further developed countries tend to have higher agricultural productivity. This increases the normative uncertainty in the dataset.

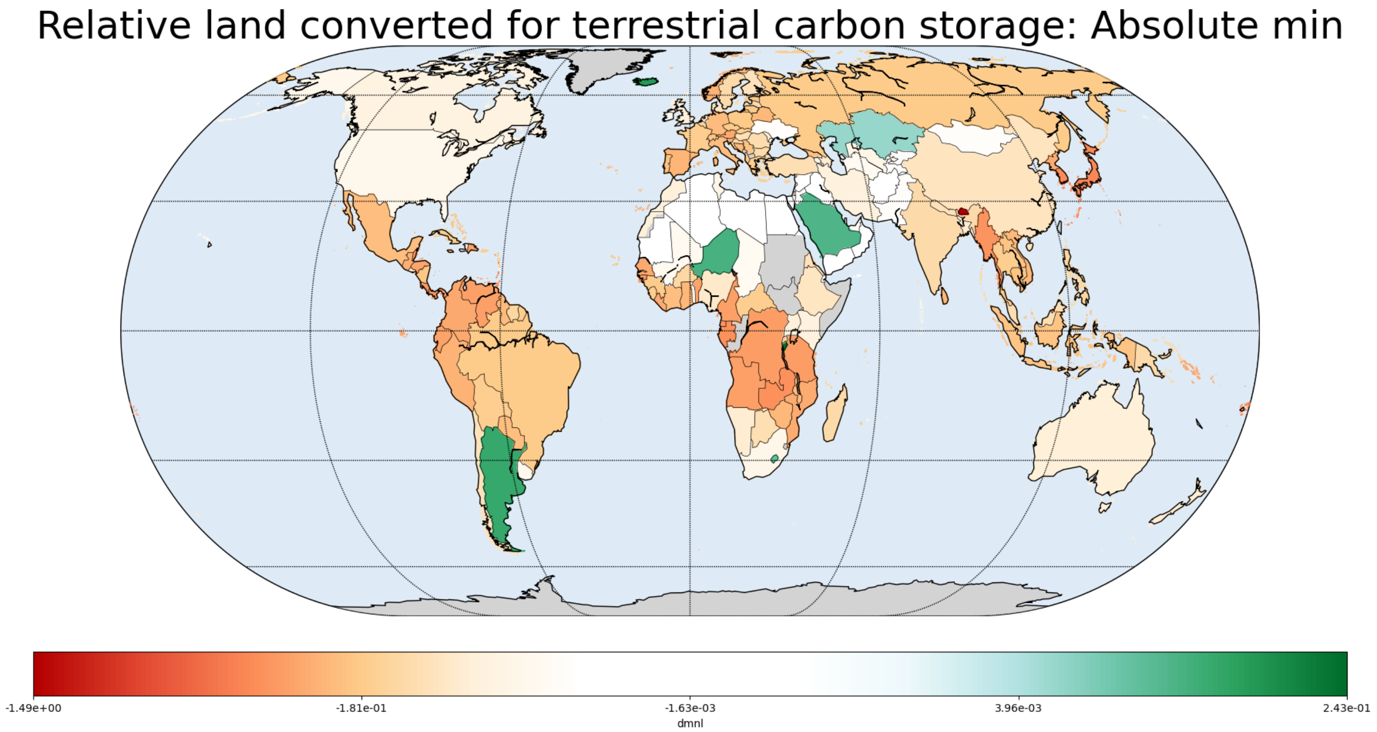


Figure 13 - Minimum land converted for terrestrial carbon storage – *Green means need to store terrestrial carbon, white means maintaining existing system, existing system can be converted - Full-sized maps in appendix*

Figure 14 compares efficiency prioritized and you-broke-it-you-fix-it. High agricultural productivity is mainly caused by water availability, economic development, and initial productivity. Typically, these countries have a far-developed economy by 2011 or experience high economic growth throughout the years. Interestingly, China and India are colored incredibly green since the model predicts that China and India will get higher agricultural productivity than the Netherlands because of their high economic growth and innovation. Because they experienced a high population growth, agricultural intensity and, thus, productivity increased substantially aswel. If the terrestrial carbon storage per capita is based on emissions per capita, Western countries would have to make substantial land sacrifices in order to compensate for their past emissions. Nevertheless, other countries, especially in the Middle East, South America, and Africa, also color red. This is because these countries often had low renewable energy share and high economic growth, leading to high emissions in 2011 – 2100. It is interesting to note how this scenario will benefit China even though their economy is growing quickly. This comes from a relatively high growing renewable share (11%) and a little historical contribution to CO2 emissions compared to Western countries (1/11th of the US).

It is essential to note that the contribution to cumulative greenhouse gas emissions will even remain primarily centralized in the Western world and Russia. This includes the potential compensation for past emissions with terrestrial carbon storage. As land available for terrestrial carbon storage in some of these countries is limited, it could be argued that therefore investing in other climate change mitigation initiatives would be even more important. Another solution could be to compensate other countries for their mitigation efforts financially.

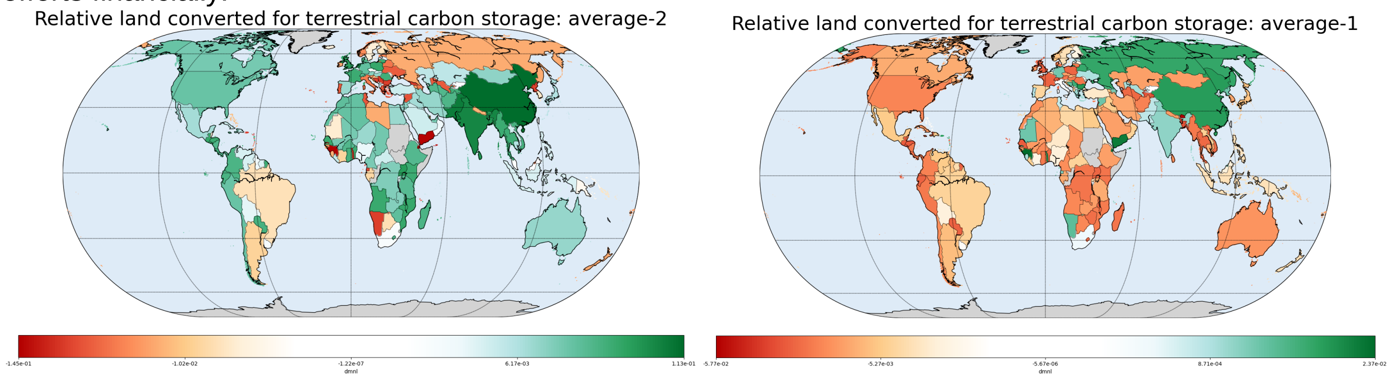


Figure 14 - Relative land converted for terrestrial carbon storage - *based on efficiency prioritized (left) and you-broke-it-you-fix-it (right) – Full-sized maps in appendix*

When exploring the sensitivity to normative uncertainties, this can be found by comparing the different climate justice principles and determining the range. The map in Figure 15 shows that the Netherlands, China, India, Yemen, Spain, and Guinea are extremely sensitive to different climate justice principles and, therefore, normative uncertainties. Other countries such as Kazakhstan, South Africa, Uruguay, Nigeria, and Finland are the least sensitive to normative uncertainties.

When diving deeper into the case of the Netherlands, China, Pakistan, and Yemen, we better understand the sensitivity and likely the preferences for different climate justice principles. In the case of the Netherlands, this sensitivity is caused by a high GDP. Therefore the Netherlands should contribute substantially according to ability-to-pay. When following efficiency prioritized, Dutch agricultural land should be kept for its high agricultural productivity. China is expected to reach a high level of domestic food security, and therefore they would have to sacrifice their land for terrestrial carbon storage according to a different interpretation of ability-to-pay, based on domestic food security. Also, the efficiency prioritized principle for China would be ideal because, with their economic growth and innovation, they are expected to reach a high level of agricultural productivity. In the case of Yemen, it is different, Yemen has low agricultural productivity, and efficiency-prioritized will lead to them converting agricultural land to forests. For Yemen, the best interpretation of ability-to-pay is the available land that could be converted for terrestrial carbon storage, since they have limited land that is suitable compared to their total land surface.

Generally, Western countries come out well when ability-to-pay is based on domestic food security. This is likely due to their historical welfare and GDP, which caused their dietary patterns to be much different from the ability to produce that food type. With their high GDP, importing these food types has never been an issue. As of 2023, China is heavily reliant on food imports. It might be surprising initially that China seems to have a low domestic food shortage. The severe shrinking in the Chinese population can explain according to the low population scenario, where the Chinese population is expected to drop from 1,3 billion to just 500 million citizens. Combined with a steep increase in agricultural productivity, this allows for domestic food security. Also, the country's sheer size is enabling China to grow all varieties of food types.

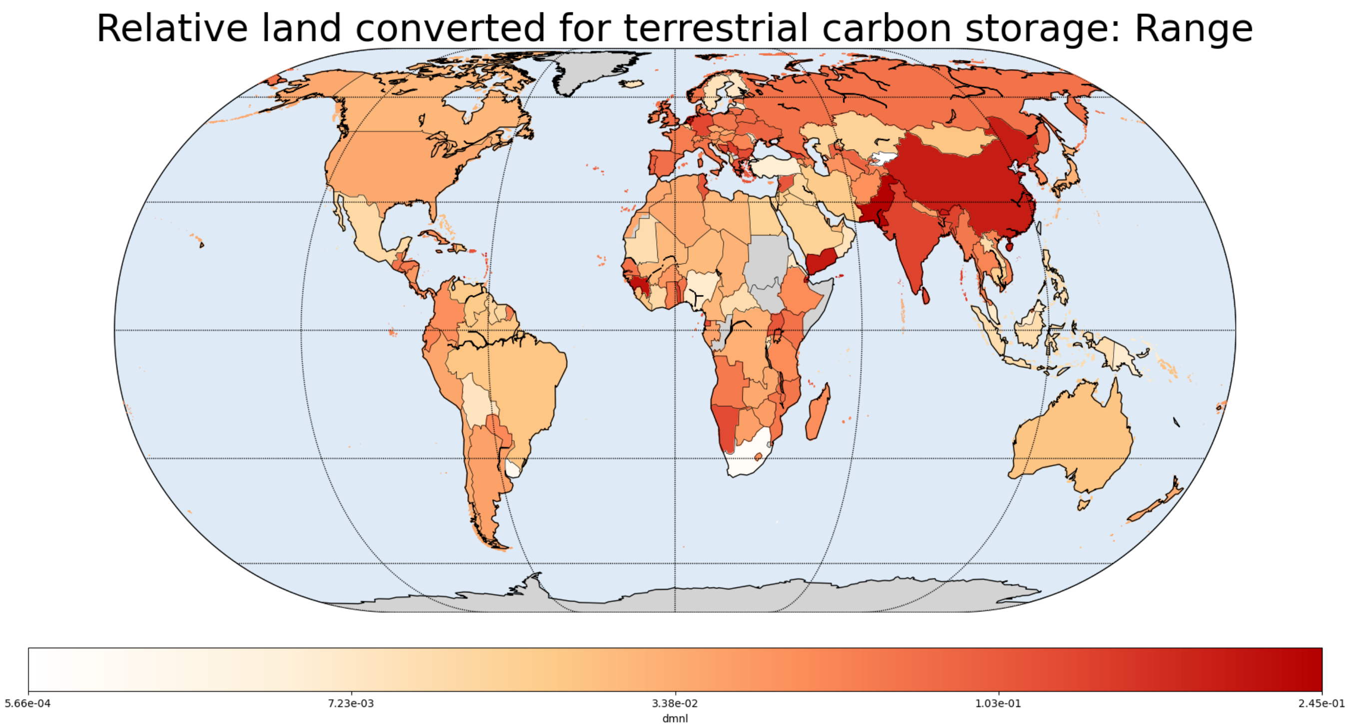


Figure 15 - Sensitivity to climate justice principles for terrestrial carbon storage – *Full-sized map shown in the appendix*

5 Conclusion

In conclusion, terrestrial carbon storage presents an opportunity that must be considered in the fight against climate change. The potential for carbon sequestration and storage - specifically in forests and wetlands - is immense. My research has highlighted this significance and pointed toward prioritizing the conservation of existing ecosystems as a highly effective strategy for mitigating climate change. Conservation is critical because the terrestrial carbon storage system's total capacity can take several decades to saturate. Even more so, wetlands will never reach a saturation point and will continue uptake. Not only is the conservation of existing terrestrial systems and recovery and creation of new forests and wetlands critical to avoid land conversion-based carbon emissions and the uptake potential of new land. Also, 'saturated' terrestrial ecosystems continue to take up more carbon as the atmospheric carbon concentration increases, causing a dampening effect in climate change. These findings suggest that investments in maintaining and enhancing existing systems could yield higher benefits than efforts on reforestation or afforestation in new areas.

This research, therefore, implores policymakers to take note. It is essential to emphasize terrestrial carbon storage when shaping climate change policy and specifically applying a swift, decisive, and global multi-stakeholder approach. Initiatives such as carbon offsetting, explored by organizations like 8 billion trees (8 billion trees, 2023) and coolearth.org (Cool Earth, 2023), could provide feasible solutions to enhance carbon sequestration. Such organizations can capitalize on the opportunity offered by terrestrial carbon storage and therefore provide a solution to bridge the period until a climate-neutral or -positive world is achieved. Ideally, these initiatives should be compared for their impact on the short-and long-term carbon system and socio-economic factors such as food supply and economic development for the local and global community. This way, the most suitable initiatives, and procedures can be followed to make optimal use of available financial and spatial means.

The EU's Nature Restoration Law (European Commission, 2023) is a step in the right direction, advocating for the conservation of existing ecosystems and restoring deteriorated systems, specifically increasing organic stocks in forests and restoring and rewetting drained peatlands of agricultural use and peat extraction sites seem to be practical aspects in terms of improving the carbon system proposed in this law. I encourage the exploration of similar policy changes globally, underscoring the importance of taking immediate action and ensuring no further deterioration of existing terrestrial carbon systems. However, it is crucial to underscore that terrestrial carbon storage is not the silver bullet solution to climate change but is a significant part of a broader toolkit. The fight against climate change demands a multi-pronged approach, integrating efforts across emission reduction, renewable energy transition, and enhanced climate resilience. It is time for the global community to leverage every tool available, including terrestrial carbon storage, to combat the existential threat of climate change.

Following the importance of terrestrial carbon storage, the question remains where and by who this should be done. My research has shown high sensitivity in land allocation for terrestrial carbon storage when comparing climate justice principles. These normative uncertainties represent potential tensions in developing a coherent global policy. In my research, certain countries are more sensitive to these normative uncertainties than others, implying that these countries have more to win or lose in political debates on perspectives of justness. I based the terrestrial carbon storage obligations distribution on cumulative historical CO2 emissions, GDP per capita, domestic food security, agricultural productivity, and land available for terrestrial carbon storage, but obviously this list can be expanded in the future.

In the group of countries that are most sensitive to the normative uncertainties, this is often caused by agricultural productivity in contrast to another factor such as ability-to-pay. Countries with a high agricultural productivity should keep their agricultural land when prioritizing agricultural productivity. Often agricultural productivity goes hand in hand with economic development and therefore a high ability-to-pay, resulting in these countries having to sacrifice their land if that principle is followed.

From an ethical standpoint, the climate justice dilemma presents no easy solutions. Balancing climate change mitigation with other critical aspects, such as food security and economic prosperity, challenges policymakers. Mainly, this struggle manifests in national debates, where these mitigation efforts may be perceived as unjust if they can cause negative consequences in fields other than climate change it is paramount for policymakers to grasp these nuanced ethical perspectives to foresee potential policy conflicts and formulate fair and equitable solutions that are non-discriminatory between the different ethical perspectives.

My analysis showed the potential to explore these non-discriminatory policies using SD combined with EMA and visualizing these results using Python. Through this approach, land that should be converted for terrestrial carbon storage, terrestrial carbon storage land that should be conserved, and land that arguably could be converted for other purposes can be discovered. I firmly believe that utilizing relatively simple integrated models capable of encapsulating normative uncertainties can complement more elaborate impact assessment models like Global Change Assessment Model (JGCRI, 2023) and IMAGE (PBL, 2023). Next to the potential to include more uncertainties in these simpler models, its simplicity also allows for a more straightforward illustration of system interactions and explanations to policymakers.

In essence, the challenge is not merely scientific or technical but is also deeply rooted in ethics and justice. It is crucial to navigating these complexities to pursue effective and equitable climate policy, something scenario exploration in combination with system dynamics modeling can contribute to.

6 Discussion

The conclusion paints a comprehensive picture of the significance of terrestrial carbon storage in mitigating climate change and the importance of climate justice principles in shaping these efforts. Nonetheless, the findings should always be put in light of the limitations of the analysis and the findings from the literature. Several aspects of the conclusion can be explored further to reduce uncertainty and make more valuable statements.

The role of terrestrial ecosystems was first discussed in the IPCC report Climate Change (IPCC, 1994), after which Siemel further explored this theory (1995). Lal (2008) defines soil carbon sequestration low hanging fruit and a suitable bridging solution until a low-emission or even emission-free society is reached. Cooper (2022) compared afforestation/reforestation with other negative emissions technologies to be more effective than other technologies but emphasizes the long duration until its potential is fully utilized. Nonetheless, there is a consensus on the difficulty of reliably quantifying the potential of terrestrial carbon storage on a global scale (Friedlingstein et al., 2022; Jiang et al., 2021; Teckentrup et al., 2021; Tian et al., 2015). This shows the difficulty of developing a reliable carbon system, even for highly specialized researchers. Matthews (2022) confirms this stating that terrestrial carbon storage is an effective way to minimize the peak in temperature increase, but also he emphasizes that terrestrial carbon storage does not replace other climate change mitigation measures, but is complementary. It is important to emphasize that betting on terrestrial carbon storage can also cause risks due to forest fires and forest disturbances (Bullock & Woodcock, 2021), and still has negative side effects to food security (Hohlwegler, 2019).

Although academic literature has no clear comparison in the effectiveness of carbon offsetting initiatives with forests, Grace (2004) sheds critical light on the Kyoto Protocol, where the conservation of existing carbon stocks was not incentivized in the Kyoto protocol. He argues that this is more critical than incentivizing afforestation or reforestation. Van Kooten (2004) explored the price of carbon offsetting but did not compare efficiency in land covers or translate these numbers to give recommendations on preferred carbon offsetting techniques with forests. Wise (2019) confirms the importance of reflecting on these factors but also warns about adding unnecessary complexities of carbon storage programs that might make it too complex, too expensive, and potentially demotivating.

While using the model has helped understand terrestrial carbon storage dynamics, it has limitations. For instance, the lack of inclusion of other GHG emissions, the absence of land cover-specific carbon flows, and missing climate-induced land cover change data all present barriers to a comprehensive understanding of terrestrial carbon storage. Additional research would be required to support and further quantify statements that are made. Further research to address these limitations could be to expand and improve the model to become more endogenous-driven and more representative of the real world with improved input data. This can be done by working closely with experts and organizations that collect and monitor climate systems. Further analysis and potential calibration with other climate models could help improve the model's reliability.

The analysis performed to explore the uncertainty space and test scenarios also has aspects that should be improved. For example, more specific terrestrial carbon interventions could be further explored and optimized over time. The current research only looks at the year 2100 and models the steps working toward that year. Still, there is no optimization for the year 2040-2075, a period in which a high food shortage is expected to occur because of a population boom. Optimizing for multiple timesteps will also help with the decision-making between different interventions because restoring wetlands can take long years and might be less impactful in the short-term but be the most valuable in the long term. Additionally, the scenarios can be further aligned with policy plans and standardized scenarios such as the Shares Socio-economic Pathways and the Representative Concentration Pathways. This also has been done by (Krause et al., 2019). This will help to align the research findings more with previous advice that policymakers receive.

Jacobs (2023) explored how negative emission technologies such as carbon sequestration in forests, wetlands, and soils are included and analyzed 29 long-term climate strategies of countries. They found that almost all countries planned to rely on these mitigation efforts to reach climate goals. Ekardt discusses the risk of efficiency considerations in climate policy (2012), also discussing that ethics is discussed but often kept vague in reports. Hohlwegler (2019) emphasizes the risk of prioritizing climate goals over other goals, such as food security. Less developed countries are most likely to suffer from this. Literature is lacking in the comparison of different ethical views on climate policy. The paper of Jafino (2021) states that using multiple moral principles side by side would be valuable and confirms that this did not yet receive much attention.

Also, in light of the second conclusion, the model's limitations must be reconsidered. As socioeconomic factors are excluded or not included as endogenous factors, the model could not provide insights into the trade-off between policies for countries. Therefore, it cannot reliably state how climate justice principles are expected to impact a country’s economy. Additionally, there is an assumption made in the model that the countries agree with the proposed climate justice principles and are willing to cohere to one of them. In reality, many different interpretations of each climate justice principle can be made, and during the analysis, I have found how different interpretations of a single climate justice principle (in this case, ability-to-pay) can have substantial differences in output. I only tested five climate justice principles, which are unlikely to fit the perspectives of all the countries. Another assumption the use-case of this research bases itself on is that countries with non-discriminatory policy interventions will cohere if the majority of the countries do not have to adhere since there is more normative uncertainty. Much more likely, there is a need to find win-win situations or have a suitable compensation method, which could also be moral. Further research could expand the socio-economic sub-models to display trade-offs and explore compensation methods. On top of that, more climate justice principles can be tested, which could be based on policy reports or political plans from countries.

7 References

8 billion trees. (2023). *8 Billion Trees: Carbon Offset Projects & Ecological Footprint Calculators*. 8 Billion Trees: Carbon Offset Projects & Ecological Footprint Calculators. https://8billiontrees.com/

Argles, A. P. K., Moore, J. R., & Cox, P. M. (2022). Dynamic Global Vegetation Models: Searching for the balance between demographic process representation and computational tractability. *PLOS Climate*, *1*(9), e0000068. https://doi.org/10.1371/journal.pclm.0000068

Auping, Kwakkel, Jan, & Pruyt, Erik. (2018). Exploring the Potential for Feeding a Changing World. *2018, Presented at the 36th International System Dynamics Conference*.

Auping, W. L. (2018). *Modelling Uncertainty: Developing and Using Simulation Models for Exploring the Consequences of Deep Uncertainty in Complex Problems*. https://doi.org/10.4233/uuid:0e0da51a-e2c9-4aa0-80cc-d930b685fc53

Bankes, S. (1993). Exploratory Modeling for Policy Analysis. *Operations Research*, *41*(3), 435–449. https://doi.org/10.1287/opre.41.3.435

Bell, C., Campbell, C., & Aoláin, F. N. (2004). Justice Discourses in Transition. *Social & Legal Studies*, *13*(3), 305–328. https://doi.org/10.1177/0964663904044997

Breiman & Ihaka. (1984, December). *Nonlinear Discriminant Analysis Via Scaling and Ace*. https://digitalassets.lib.berkeley.edu/sdtr/ucb/text/40.pdf

Brzezina, N., Kopainsky, B., & Mathijs, E. (2016). Can Organic Farming Reduce Vulnerabilities and Enhance the Resilience of the European Food System? A Critical Assessment Using System Dynamics Structural Thinking Tools. *Sustainability*, *8*(10), Article 10. https://doi.org/10.3390/su8100971

Bullock, E. L., & Woodcock, C. E. (2021). Carbon loss and removal due to forest disturbance and regeneration in the Amazon. *Science of the Total Environment*, *764*. Scopus. https://doi.org/10.1016/j.scitotenv.2020.142839

Caney, S. (2009). Climate Change and the Future: Discounting for Time, Wealth, and Risk. *Journal of Social Philosophy*, *40*(2), 163–186. https://doi.org/10.1111/j.1467-9833.2009.01445.x

Carlowicz, Michael. (2012, January 9). *Seeing Forests for the Trees and the Carbon: Mapping the World's Forests in Three Dimensions* [Text.Article]. NASA Earth Observatory. https://earthobservatory.nasa.gov/features/ForestCarbon#:%7E:text=They%20cover%20about%2030%20percent,percent%20of%20the%20Earth%27s%20land

Ciais, Sabine, C., & Al, E. (2018). *Carbon and Other Biogeochemical Cycles*. https://www.ipcc.ch/site/assets/uploads/2018/02/WG1AR5_Chapter06_FINAL.pdf

Cool Earth. (2023). *Cool Earth | Protect Rainforest | Fight The Climate Crisis*. Cool Earth. https://www.coolearth.org/

Cooper, J., Dubey, L., & Hawkes, A. (2022). *Life cycle assessment of negative emission technologies for effectiveness in carbon sequestration*. *105*, 357–361. Scopus. https://doi.org/10.1016/j.procir.2022.02.059

D'Alessandro, S., Cieplinski, A., Distefano, T., & Dittmer, K. (2020). Feasible alternatives to green growth. *Nature Sustainability*, *3*(4), Article 4. https://doi.org/10.1038/s41893-020-0484-y

Davidson, N. C., & Davidson, N. C. (2014). How much wetland has the world lost? Long-term and recent trends in global wetland area. *Marine and Freshwater Research*, *65*(10), 934–941. https://doi.org/10.1071/MF14173

Dayathilake, D. D. T. L., Lokupitiya, E., & Wijeratne, V. P. I. S. (2020). Estimation of aboveground and belowground carbon stocks in urban freshwater wetlands of Sri Lanka. *Carbon Balance and Management*, *15*(1), 17. https://doi.org/10.1186/s13021-020-00152-5

Ekardt, F. (2012). A Critical Review of "Efficiency Ethics": The Case of Climate Economics. *Law and Philosophy Library*, *98*, 181–210. Scopus. https://doi.org/10.1007/978-94-007-1869-2_9

Erb, K.-H., Luyssaert, S., Meyfroidt, P., Pongratz, J., Don, A., Kloster, S., Kuemmerle, T., Fetzel, T., Fuchs, R., Herold, M., Haberl, H., Jones, C. D., Marín-Spiotta, E., McCallum, I., Robertson, E., Seufert, V., Fritz, S., Valade, A., Wiltshire, A., & Dolman, A. J. (2017). Land management: Data availability and process understanding for global change studies. *Global Change Biology*, *23*(2), 512–533. https://doi.org/10.1111/gcb.13443

European Commission. (2023, June 7). *The EU #NatureRestoration Law*. https://environment.ec.europa.eu/topics/nature-and-biodiversity/nature-restoration-law_en

FAOSTAT. (2017). *FAOSTAT*. https://www.fao.org/faostat/en/#home

Forrester. (1961). *Industrial dynamics*. http://www.laprospective.fr/dyn/francais/memoire/autres_textes_de_la_prospective/autres_ouvrages_numerises/industrial-dynamics-forrester-1961.pdf

Forrester, J. W., Mass, N. J., & Ryan, C. J. (1976). The system dynamics national model: Understanding socio-economic behavior and policy alternatives. *Technological Forecasting and Social Change*, *9*(1), 51–68. https://doi.org/10.1016/0040-1625(76)90044-5

Forrester & Senge. (1980). *Tests for building confidence in System Dynamics models.pdf*. https://www.albany.edu/faculty/gpr/PAD724/724WebArticles/ForresterSengeValidation.pdf

Friedlingstein, P., Jones, M. W., O'Sullivan, M., Andrew, R. M., Bakker, D. C. E., Hauck, J., Le Quéré, C., Peters, G. P., Peters, W., Pongratz, J., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Anthoni, P., Bates, N. R., Becker, M., Bellouin, N., … Zeng, J. (2022). Global Carbon Budget 2021. *Earth System Science Data*, *14*(4), 1917–2005. https://doi.org/10.5194/essd-14-1917-2022

Friedman, J. H., & Fisher, N. I. (1999). Bump hunting in high-dimensional data. *Statistics and Computing*, *9*(2), 123–143. https://doi.org/10.1023/A:1008894516817

Füssel, H.-M. (2010). How inequitable is the global distribution of responsibility, capability, and vulnerability to climate change: A comprehensive indicator-based assessment. *Global Environmental Change*, *20*(4), 597–611. https://doi.org/10.1016/j.gloenvcha.2010.07.009

German Advisory Council, on Global Change, (WBGU), & Kruse-Graumann, L. (1998). *The Accounting of Biological Sinks and Sources Under the Kyoto Protocol*. WBGU.

Grace, J. (2004). Understanding and managing the global carbon cycle. *Journal of Ecology*, *92*(2), 189–202. Scopus. https://doi.org/10.1111/j.0022-0477.2004.00874.x

Green, C., & Byrne, K. A. (2004). Biomass: Impact on Carbon Cycle and Greenhouse Gas Emissions. In C. J. Cleveland (Ed.), *Encyclopedia of Energy* (pp. 223–236). Elsevier. https://doi.org/10.1016/B0-12-176480-X/00418-6

Heyward, M. (2007). Equity and international climate change negotiations: A matter of perspective. *Climate Policy*, *7*(6), 518–534. https://doi.org/10.1080/14693062.2007.9685674

Hohlwegler, P. (2019). Moral Conflicts of several "green" terrestrial Negative Emission Technologies regarding the Human Right to Adequate Food—A Review. *Advances in Geosciences*, *49*, 37–45. Scopus. https://doi.org/10.5194/adgeo-49-37-2019

Hussey, K., & Pittock, J. (2012). The Energy–Water Nexus: Managing the Links between Energy and Water for a Sustainable Future. *Ecology and Society*, *17*(1). https://doi.org/10.5751/ES-04641-170131

IPCC. (1994). Climate change, 1994: Radiative forcing of climate change and an evaluation of the IPCC IS92 emission scenarios. *Choice Reviews Online*, *33*(07), 33-3969-33–3969. https://doi.org/10.5860/CHOICE.33-3969

IPCC. (2018). *The Carbon Cycle and Atmospheric Carbon Dioxide—IPCC*. https://www.ipcc.ch/report/ar3/wg1/the-carbon-cycle-and-atmospheric-carbon-dioxide/

IPCC. (2020). *Summary for Policymakers—Special Report on Climate Change and Land*. https://www.ipcc.ch/srccl/chapter/summary-for-policymakers/

IPCC. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability | Climate Change 2022: Impacts, Adaptation and Vulnerability*. https://www.ipcc.ch/report/ar6/wg2/

Jacobs, H., Gupta, A., & Möller, I. (2023). Governing-by-aspiration? Assessing the nature and implications of including negative emission technologies (NETs) in country long-term climate strategies. *Global Environmental Change*, *81*. Scopus. https://doi.org/10.1016/j.gloenvcha.2023.102691

Jafino, B. A., Kwakkel, J. H., & Taebi, B. (2021). Enabling assessment of distributive justice through models for climate change planning: A review of recent advances and a research agenda. *WIREs Climate Change*, *12*(4), e721. https://doi.org/10.1002/wcc.721

Janowiak, M., Connelly, W. J., Dante-Wood, K., Domke, G. M., Giardina, C., Kayler, Z., Marcinkowski, K., Ontl, T., Rodriguez-Franco, C., Swanston, C., Woodall, C. W., & Buford, M. (2017). Considering Forest and Grassland Carbon in Land Management. *General Technical Report, Washington Office*, *95*. https://doi.org/10.2737/WO-GTR-95

JGCRI. (2023). *Release GCAM version 4.4.1 · JGCRI/gcam-core*. GitHub. https://github.com/JGCRI/gcam-core/releases/tag/gcam-v4.4.1

Jiang, L., Liang, J., Lu, X., Hou, E., Hoffman, F. M., & Luo, Y. (2021). Country-level land carbon sink and its causing components by the middle of the twenty-first century. *Ecological Processes*, *10*(1). Scopus. https://doi.org/10.1186/s13717-021-00328-y

Jin, H. (2022). Rawlsian and Confucian Distributive Justice and the Worst Off. *Philosophia*. https://doi.org/10.1007/s11406-022-00486-z

Kolm, S.-C. (1977). Multidimensional Egalitarianisms. *The Quarterly Journal of Economics*, *91*(1), 1–13. https://doi.org/10.2307/1883135

Konow, J. (2001). Fair and square: The four sides of distributive justice. *Journal of Economic Behavior & Organization*, *46*(2), 137–164. https://doi.org/10.1016/S0167-2681(01)00194-9

Krause, A., Haverd, V., Poulter, B., Anthoni, P., Quesada, B., Rammig, A., & Arneth, A. (2019). Multimodel Analysis of Future Land Use and Climate Change Impacts on Ecosystem Functioning. *Earth's Future*, *7*(7), 833–851. Scopus. https://doi.org/10.1029/2018EF001123

Kwakkel, Auping, & Pruyt. (2013). Dynamic scenario discovery under deep uncertainty: The future of copper. *Technological Forecasting and Social Change*, *80*(4), 789–800. https://doi.org/10.1016/j.techfore.2012.09.012

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, *96*, 239–250. https://doi.org/10.1016/j.envsoft.2017.06.054

Kwakkel, J. H., & Pruyt, E. (2013). Using System Dynamics for Grand Challenges: The ESDMA Approach. *Systems Research and Behavioral Science*, *32*(3), 358–375. https://doi.org/10.1002/sres.2225

Lal, R. (2008). Carbon sequestration. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1492), 815–830. https://doi.org/10.1098/rstb.2007.2185

Lamont, J., & Favor, C. (2017). Distributive Justice. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy* (Winter 2017). Metaphysics Research Lab, Stanford University. https://plato.stanford.edu/archives/win2017/entries/justice-distributive/

Lane, D. C. (2000). Diagramming conventions in system dynamics. *Journal of the Operational Research Society*, *51*(2), 241–245. https://doi.org/10.1057/palgrave.jors.2600864

Lane, D. C. (2001). Rerum cognoscere causas: Part I — How do the ideas of system dynamics relate to traditional social theories and the voluntarism/determinism debate? *System Dynamics Review*, *17*(2), 97–118. https://doi.org/10.1002/sdr.209

Matthews, H. D., Zickfeld, K., Dickau, M., MacIsaac, A. J., Mathesius, S., Nzotungicimpaye, C.-M., & Luers, A. (2022). Temporary nature-based carbon removal can lower peak warming in a well-below 2 °C scenario. *Communications Earth and Environment*, *3*(1). Scopus. https://doi.org/10.1038/s43247-022-00391-z

Mi, H., Qiao, G., Wang, W., & Hong, Y. (2019). Analysis of urban growth from 1960 to 2015 using historical DISP and Landsat time series data in Shanghai. *Arabian Journal of Geosciences*, *12*(7), 250. https://doi.org/10.1007/s12517-019-4420-2

Muizniecea, I., Dace, E., & Blumberga, D. (2015). Dynamic Modeling of the Environmental and Economic Aspects of Bio-Resources from Agricultural and Forestry Wastes. *Procedia Earth and Planetary Science*, *15*, 806–812. https://doi.org/10.1016/j.proeps.2015.08.129

Murdiyarso, D., Purbopuspito, J., Kauffman, J. B., Warren, M. W., Sasmito, S. D., Donato, D. C., Manuri, S., Krisnawati, H., Taberima, S., & Kurnianto, S. (2015). The potential of Indonesian mangrove forests for global climate change mitigation. *Nature Climate Change*, *5*(12), Article 12. https://doi.org/10.1038/nclimate2734

NASA Global Climate. (2022). *Carbon Dioxide Concentration | NASA Global Climate Change*. Climate Change: Vital Signs of the Planet. https://climate.nasa.gov/vital-signs/carbon-dioxide

Niewöhner, J., Bruns, A., Haberl, H., Hostert, P., Krueger, P., Lauk, C., Lutz, J., Müller, D., & Nielsen, J. (2016). *Land Use Competition*. https://doi.org/10.18452/19346

OECD. (2021). *Land use*. https://stats.oecd.org/Index.aspx?DataSetCode=LAND_USE#

Okereke, C. (2010). Climate justice and the international regime. *WIREs Climate Change*, *1*(3), 462–474. https://doi.org/10.1002/wcc.52

Our World in Data. (2023). *Who has contributed most to global CO2 emissions?* Our World in Data. https://ourworldindata.org/contributed-most-global-co2

Page, E. A. (2007). Fairness on the Day after Tomorrow: Justice, Reciprocity and Global Climate Change. *Political Studies*, *55*(1), 225–242. https://doi.org/10.1111/j.1467-9248.2007.00649.x

Pazner, E. A., & Schmeidler, D. (1978). Egalitarian Equivalent Allocations: A New Concept of Economic Equity. *The Quarterly Journal of Economics*, *92*(4), 671. https://doi.org/10.2307/1883182

PBL. (2023). *Welcome to IMAGE 3.2 Documentation—IMAGE*. https://models.pbl.nl/image/index.php/Welcome_to_IMAGE_3.2_Documentation

Pesch, U., Correljé, A., Cuppen, E., & Taebi, B. (2017). Energy justice and controversies: Formal and informal assessment in energy projects. *Energy Policy*, *109*, 825–834. https://doi.org/10.1016/j.enpol.2017.06.040

Petrokofsky, G., Kanamaru, H., Achard, F., Goetz, S. J., Joosten, H., Holmgren, P., Lehtonen, A., Menton, M. C., Pullin, A. S., & Wattenbach, M. (2012). Comparison of methods for measuring and assessing carbon stocks and carbon stock changes in terrestrial carbon pools. How do the accuracy and precision of current methods compare? A systematic review protocol. *Environmental Evidence*, *1*(1), 6. https://doi.org/10.1186/2047-2382-1-6

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B. L., Dietrich, J. P., Doelmann, J. C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., … Vuuren, D. P. van. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change*, *42*, 331–345. https://doi.org/10.1016/j.gloenvcha.2016.10.002

Pruyt, E. (2007). *Dealing with uncertainties? Combining System Dynamics with Multiple Criteria Decision Analysis or with Exploratory Modelling*.

Pruyt, E. (2010). *Using Small Models for Big Issues: Exploratory System Dynamics Modelling and Analysis for Insightful Crisis Management*.

Pruyt, E., & de Sitter, G. (2008). “Food or Energy?” Is that the question? *Proceedings of the 26th International Conference of the System Dynamics Society*, 1–20.

Reichstein, M., & Carvalhais, N. (2019). Aspects of Forest Biomass in the Earth System: Its Role and Major Unknowns. *Surveys in Geophysics*, *40*(4), 693–707. https://doi.org/10.1007/s10712-019-09551-x

Schiemel, D. S. (1995). Terrestrial ecosystems and the carbon cycle. *Global Change Biology*, *1*(1), 77–91. Scopus. https://doi.org/10.1111/j.1365-2486.1995.tb00008.x

Schlosberg. (2009). *Climate Justice Beyond Equity: The Flourishing of Human and Non-Human Communities*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1449681

Schlosberg, D., & Collins, L. B. (2014). From environmental to climate justice: Climate change and the discourse of environmental justice. *WIREs Climate Change*, *5*(3), 359–374. https://doi.org/10.1002/wcc.275

Shavazipour, B., Kwakkel, J. H., & Miettinen, K. (2021). Multi-scenario multi-objective robust optimization under deep uncertainty: A posteriori approach. *Environmental Modelling & Software*, *144*, 105134. https://doi.org/10.1016/j.envsoft.2021.105134

Shields, L. (2012). The Prospects for Sufficientarianism. *Utilitas*, *24*(1), 101–117. https://doi.org/10.1017/S0953820811000392

Stave, K. A., & Kopainsky, B. (2015). A system dynamics approach for examining mechanisms and pathways of food supply vulnerability. *Journal of Environmental Studies and Sciences*, *5*(3), 321–336. https://doi.org/10.1007/s13412-015-0289-x

Steinmann, P. (2018). *Behavior-Based Scenario Discovery: Induction of decision-relevant input subspaces from nonlinear model outputs using time series clustering*. https://repository.tudelft.nl/islandora/object/uuid%3Acb4fee52-e23f-41d3-9c63-7ca7ec948304

Sterman, J. (2000). Business Dynamics, System Thinking and Modeling for a Complex World. *Http://Lst-Iiep.Iiep-Unesco.Org/Cgi-Bin/Wwwi32.Exe/[In=epidoc1.in]/?T2000=013598/(100)*, *19*.

Taebi, B., Kwakkel, J. H., & Kermisch, C. (2020). Governing climate risks in the face of normative uncertainties. *WIREs Climate Change*, *11*(5), e666. https://doi.org/10.1002/wcc.666

Teckentrup, L., De Kauwe, M. G., Pitman, A. J., Goll, D. S., Haverd, V., Jain, A. K., Joetzjer, E., Kato, E., Lienert, S., Lombardozzi, D., McGuire, P. C., Melton, J. R., Nabel, J. E. M. S., Pongratz, J., Sitch, S., Walker, A. P., & Zaehle, S. (2021). Assessing the representation of the Australian carbon cycle in global vegetation models. *Biogeosciences*, *18*(20), 5639–5668. Scopus. https://doi.org/10.5194/bg-18-5639-2021

Tian, H., Lu, C., Yang, J., Banger, K., Huntzinger, D. N., Schwalm, C. R., Michalak, A. M., Cook, R., Ciais, P., Hayes, D., Huang, M., Ito, A., Jain, A. K., Lei, H., Mao, J., Pan, S., Post, W. M., Peng, S., Poulter, B., … Zeng, N. (2015). Global patterns and controls of soil organic carbon dynamics as simulated by multiple terrestrial biosphere models: Current status and future directions. *Global Biogeochemical Cycles*, *29*(6), 775–792. Scopus. https://doi.org/10.1002/2014GB005021

Törnblom, K. Y., & Vermunt, R. (1999). An Integrative Perspective on Social Justice: Distributive and Procedural Fairness Evaluations of Positive and Negative Outcome Allocations. *Social Justice Research*, *12*(1), 39–64. https://doi.org/10.1023/A:1023226307252

Trindade, A. A. C. (2017). *The Evolving Law on Conservation of Living Species* (pp. 635–672). Brill Nijhoff. https://doi.org/10.1163/9789004340046_007

UNFCCC. (2023). *The Paris Agreement | UNFCCC*. https://unfccc.int/process-and-meetings/the-paris-agreement

United Nations. (2022). *World Wetlands Day*. United Nations; United Nations. https://www.un.org/en/observances/world-wetlands-day

United Nations. (2023). *World Population Prospects—Population Division—United Nations*. https://population.un.org/wpp/

van den Berg, N. J., van Soest, H. L., Hof, A. F., den Elzen, M. G. J., van Vuuren, D. P., Chen, W., Drouet, L., Emmerling, J., Fujimori, S., Höhne, N., Kõberle, A. C., McCollum, D., Schaeffer, R., Shekhar, S., Vishwanathan, S. S., Vrontisi, Z., & Blok, K. (2020). Implications of various effort-sharing approaches for national carbon budgets and emission pathways. *Climatic Change*, *162*(4), 1805–1822. https://doi.org/10.1007/s10584-019-02368-y

van Kooten, G. C., Eagle, A. J., Manley, J., & Smolak, T. (2004). How costly are carbon offsets? A meta-analysis of carbon forest sinks. *Environmental Science and Policy*, *7*(4), 239–251. Scopus. https://doi.org/10.1016/j.envsci.2004.05.006

Ventena Systems. (2023). *Vensim*. https://vensim.com/

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., & Watson, J. E. M. (2016). Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. *Nature Communications*, *7*(1), Article 1. https://doi.org/10.1038/ncomms12558

Vermunt, R., & Törnblom, K. (1996). Introduction: Distributive and procedural justice. *Social Justice Research*, *9*(4), 305–310. https://doi.org/10.1007/BF02196987

Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature Communications*, *12*(1), Article 1. https://doi.org/10.1038/s41467-021-22702-2

Wise, L., Marland, E., Marland, G., Hoyle, J., Kowalczyk, T., Ruseva, T., Colby, J., & Kinlaw, T. (2019). Optimizing sequestered carbon in forest offset programs: Balancing accounting stringency and participation. *Carbon Balance and Management*, *14*(1). Scopus. https://doi.org/10.1186/s13021-019-0131-y

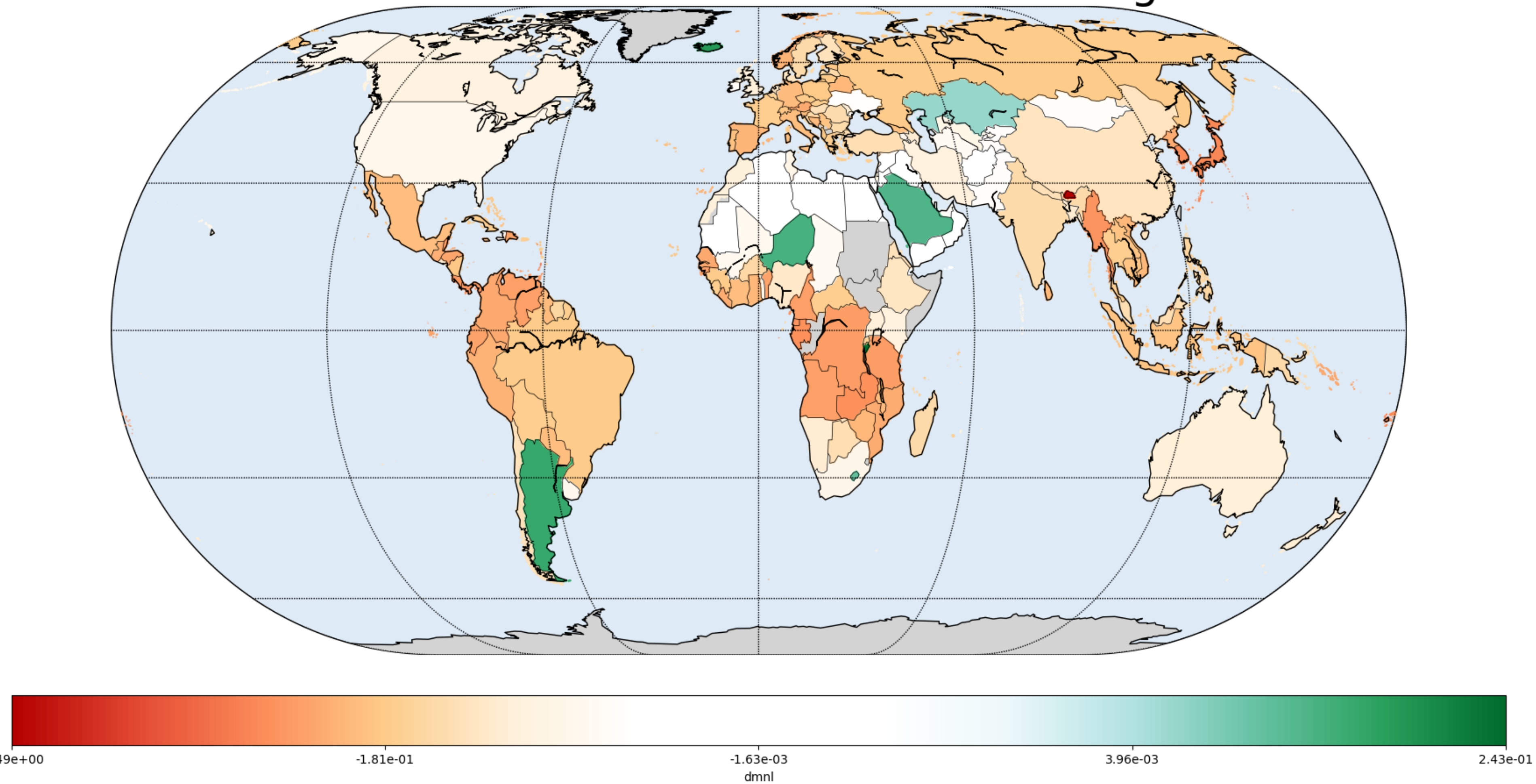
World Bank. (2023a). *World Bank Climate Change Knowledge Portal*. https://climateknowledgeportal.worldbank.org/

World Bank. (2023b). *World Bank Open Data*. World Bank Open Data. https://data.worldbank.org

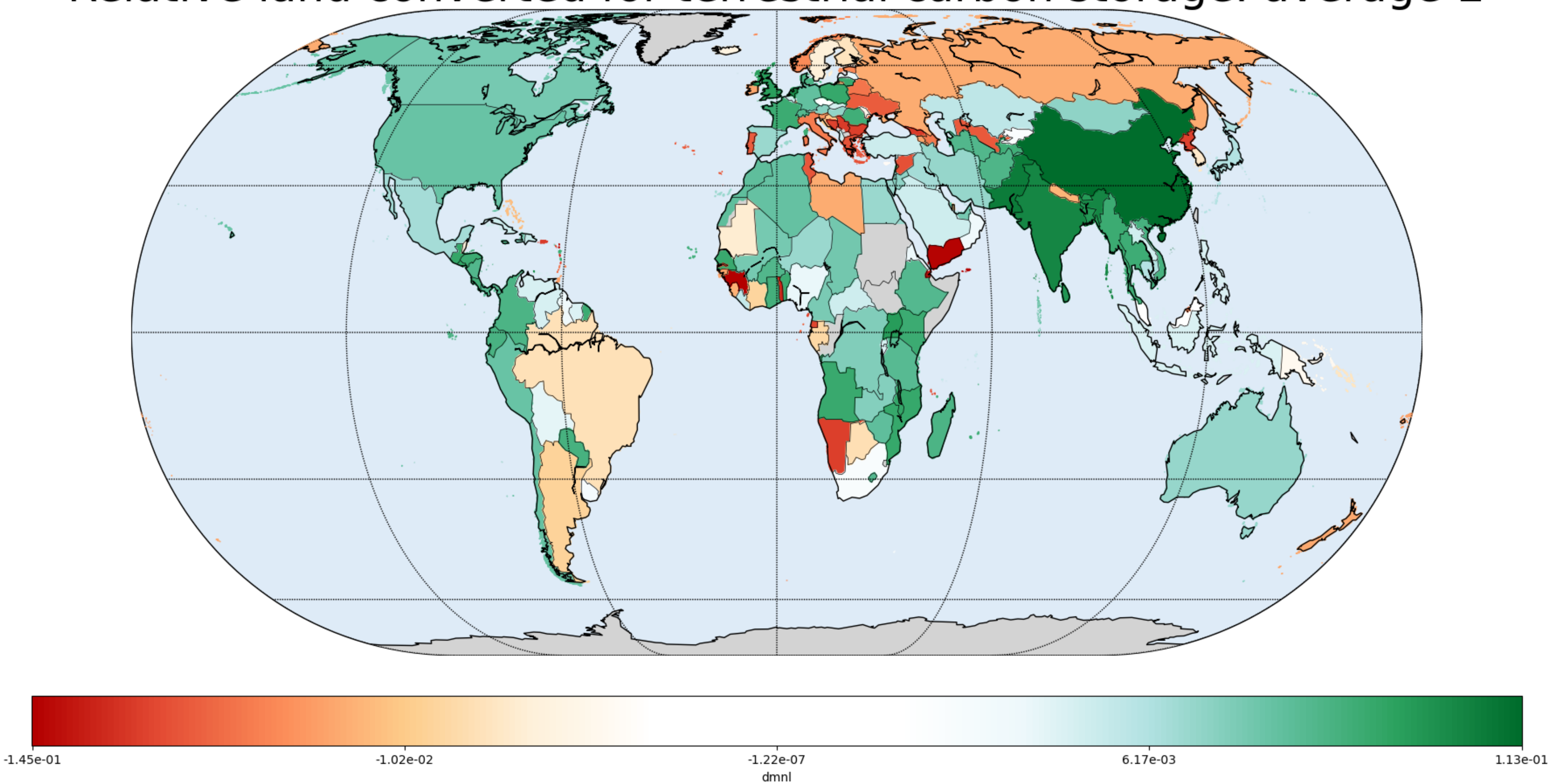
Yirdaw, E., Tigabu, M., & Monge, A. (2017). Rehabilitation of degraded dryland ecosystems – review. *Silva Fennica*, *51*(1B). https://www.silvafennica.fi/article/1673

Appendix – full-sized maps

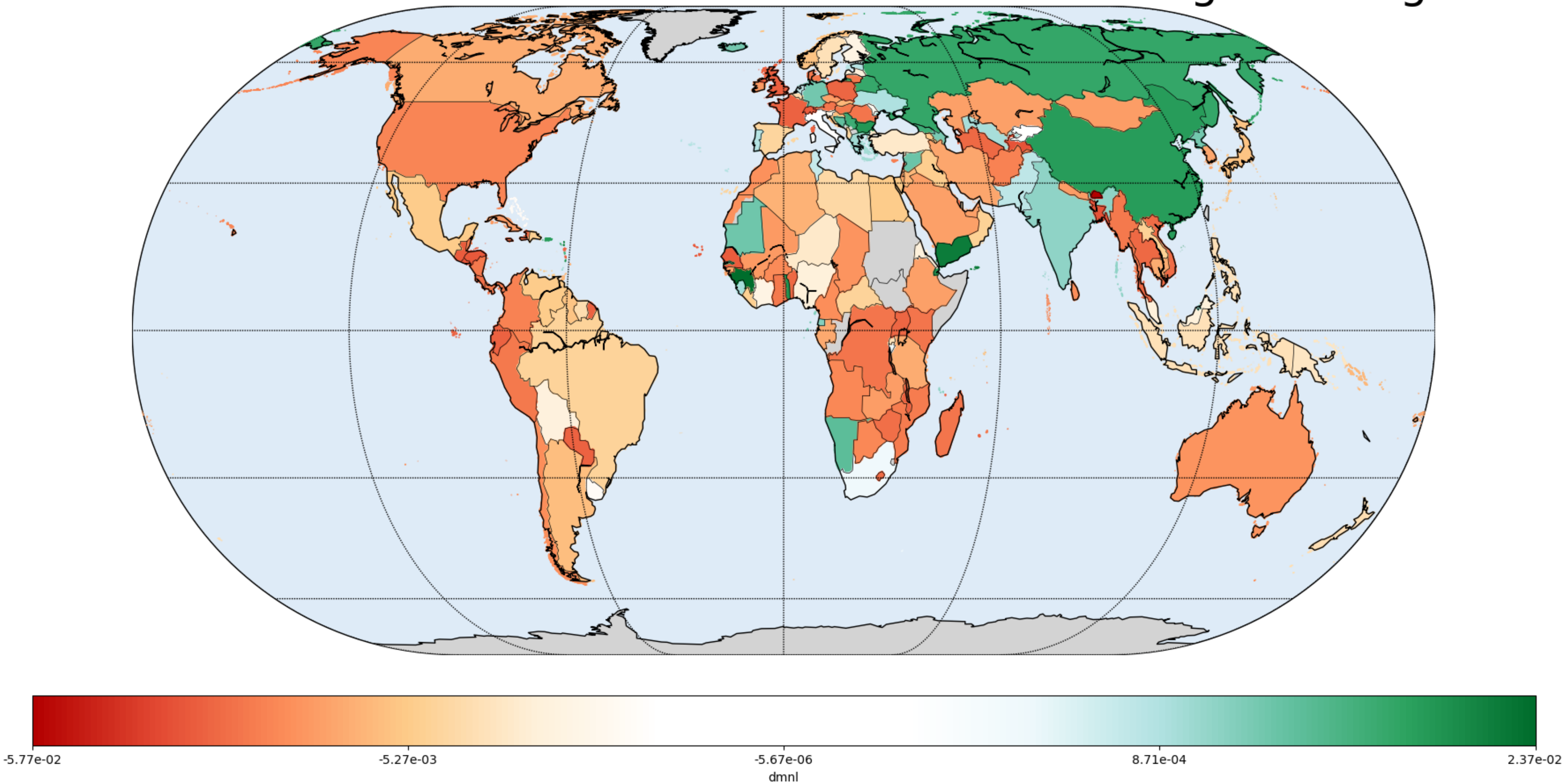
Relative land converted for terrestrial carbon storage: Absolute min



Relative land converted for terrestrial carbon storage: average-2



Relative land converted for terrestrial carbon storage: average-1



Relative land converted for terrestrial carbon storage: Range