Title
Modeling the Economic and Environmental Impacts of Land Scarcity Under Deep Uncertainty

Journal
Earth's Future, 10(2)

ISSN
2328-4277

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Publication Date
2022-02-01

DOI
10.1029/2021ef002466

Earth's Future

RESEARCH ARTICLE

10.1029/2021EF002466

Special Section:
Modeling MultiSector Dynamics to Inform Adaptive Pathways

Key Points:

- Growing food demands coupled with expanded protected lands and bioenergy production intensify land scarcity impacts across sectors
- Impacts are largely driven by deeply uncertain human development pathways
- Tradeoffs between sectors and across regions necessitate studying land management in the context of multi-sector dynamics

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Dolan, F., Lamontagne, J., Calvin, K., Snyder, A., Narayan, K. B., Di Vittorio, A. V., & Vernon, C. R. (2022). Modeling the economic and environmental impacts of land scarcity under deep uncertainty. *Earth's Future*, *10*, e2021EF002466. https://doi.org/10.1029/2021EF002466

Received 28 SEP 2021
Accepted 8 JAN 2022

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Modeling the Economic and Environmental Impacts of Land Scarcity Under Deep Uncertainty

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Abstract Land scarcity is increasing over time, driven by complex multisector dynamics. The impacts of land scarcity on the economy and environment are multi-faceted and regional, so any action to convert land will contain inherent tradeoffs. These impacts are complicated by the deeply uncertain evolution of the various sectors influencing land scarcity. A need therefore exists to provide multi-metric and multi-sector assessments that are robust to myriad uncertainties. Land conservation effectively limits the supply of productive land, while biofuel consumption increases the demand and competition for that land, and how these dynamics individually and jointly propagate to economic and environmental impacts is an important open question. To address this, we adopt the Global Change Analysis Model (GCAM) that has representations of various important systems including the climate, macroeconomic, energy, agriculture and land, and water resources systems. Various scenarios of increased land demand (from biofuels) and decreased land supply (from conservation) under various socioeconomic scenarios drawn from the SSPs were simulated using GCAM. We find that while biofuel consumption and land conservation reduce carbon emissions, this comes at the cost of higher food prices, reduced crop production, and increased water withdrawals. Additionally, some regions experience these tradeoffs more severely than others and are more heavily impacted from the same biofuel mandate or by an additional percent of protected land. These and other findings highlight the importance of multisector modeling frameworks that capture many cross-sector linkages, and acknowledge the important uncertainties confronting the human-Earth system when making any analysis of land scarcity impacts.

1. Introduction

Productive land is a scarce resource with a decreasing supply (Gomiero, 2016) but ever growing demands (Gomiero, 2016; Lambin & Meyfroidt, 2011). Increasing population and wealth cause greater demand for crops, meat, and other agricultural products and therefore for the water and energy resources needed to produce these products. At the same time, non-commercial land is an integral part of most environmental objectives. Land conservation is necessary to maintain biodiversity and healthy stable ecosystems (Thompson et al., 2009), and forests and soils are valuable carbon sinks that aid in mitigating severe climate change (Asner et al., 2004; Lal, 2004). These services improve the long-term quality of life on Earth and help achieve the relatively near-term goals of international environmental agreements such as the Convention on Biodiversity and the Paris Accords. The competing multi-sector demands for land (Carrasco et al., 2017; Dooley et al., 2018; Grass et al., 2020; Meyfroidt, 2018) emphasize the importance of modeling land scarcity in the context of the complex coupled human-Earth system. To more fully understand the multisector dynamics that drive land scarcity and its impacts, multiple metrics should be evaluated so that synergies and tradeoffs between competing sectors are made known (Kroll et al., 2019; van Vuuren et al., 2015). Further, these dynamics should be analyzed in the context of the abundant uncertainty present in the system. Dynamics may shift depending on the circumstances and it is important to understand the drivers of these dynamical shifts so that planners can make decisions that are robust to future changes. Other land use studies assess multiple impact metrics without explicitly accounting for future uncertainty (Kroll et al., 2019; van Vuuren et al., 2015) or assess economic (Waldron et al., 2020) or environmental (Borrelli et al., 2020; Mouratiadou et al., 2016) impacts under uncertainty, but few studies implement all of these elements (Gao & Bryan, 2017). Considering only one metric may lead to myopic decisions and high regret, whereas failing to account for uncertainty can lead to decisions that leave the population vulnerable to high losses (Reckhow, 1994).

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This study addresses these issues by using a global integrated multi-sector model to analyze a suite of economic and environmental metrics under a wide range of uncertainties to understand the impacts of land scarcity. Specifically, this study aims to uncover (a) the economic and environmental implications of land scarcity, (b) the drivers of land scarcity impacts, and (c) the tradeoffs and synergies between impacts in different sectors. We use a leading integrated assessment model (Krey et al., 2014) to evaluate the impacts of constraints that induce land scarcity through different channels: biofuel production changes the amount of land demanded for a specific purpose while land conservation changes the supply of land that is available for development.

Both biofuel production and land conservation have increased historically and increase further in the future under many modeled pathways (Masson-Delmotte et al., 2018). More ambitious land conservation efforts have been discussed and increasingly implemented through the "30 by 30" initiative, where countries pledge to protect 30% of their land and oceans by 2030 (Showstack, 2020). While the long-term environmental effects of land conservation are clearly desirable, lawmakers may be concerned that prohibiting development will harm local economies (Turkewitz, 2017). A meta-analysis of 171 protected area case studies found that protected areas typically benefit local economies but negatively impact the livelihood of communities' inhabitants (Oldekop et al., 2016). These impacts were highly regionally dependent, but were often positive if the protected areas were co-managed by the state and local community and if the conservation program maintained cultural and livelihood benefits (e.g., by allowing the sustainable use of natural resources for subsistence farming). At the global scale, a comprehensive economic impact study led by the International Institute for Applied Systems Analysis found net benefits from protecting 30% of land on Earth (Waldron et al., 2020). While this study incorporated uncertainty by simulating a range of conservation scenarios in four separate general equilibrium models, a research gap exists in the conservation literature of studying socioeconomic and environmental uncertainties and their impacts on metrics of interest.

There is an extensive literature devoted to assessing the environmental and economic impacts of different biofuel policy implementations (Chen et al., 2017; Hertel et al., 2010; Popp et al., 2014; Weng et al., 2019; Zhao et al., 2020). As biofuel is primarily derived from plant matter, mandating or subsidizing its consumption is highly favorable to agricultural producers, which in turn often renders those policies politically tenable (Hertel, 2011; Lawrence, 2010). However, bioenergy use is controversial because of its ambiguous effect on the global food system, land use, and water withdrawals (Ai et al., 2021; Hasegawa et al., 2018). First generation biofuels (i.e., agricultural crops grown for use as fuel) are still the most widely used form of bioenergy and have been shown to cause crop price increases in models (Rajagopal et al., 2009; Wise et al., 2014), although this result has seen mixed support from studies analyzing real-world data (Renzaho et al., 2017; Shrestha et al., 2019; Zilberman et al., 2013). A consistent finding, however, is that the second generation of biofuels (e.g., crop residue, switchgrass, and industrial waste) are more economical than their predecessors and result in fewer emissions from land use change if implemented on marginal or otherwise unused land (Bhatia et al., 2017; Fargione et al., 2008; Robertson et al., 2017).

Both land conservation and biofuel production have implications for the land system, restricting the amount of land available for other uses. Hereafter, we will refer to land conservation and biofuel production as "constraints" to emphasize the implication they both share. Land is a binding constraint to development as it is a nonsubstitutable good. While fertilizer and other agricultural technologies may enable production onto previously unsuitable land, there is ultimately a limit on the total area of land available for development. One estimate has shown that the reserve of all productive land may be exhausted in the near future (Lambin & Meyfroidt, 2011) while other work maintains that land and agricultural prices will soar and reduce demand before the supply of productive land is exhausted (Hertel, 2011).

As nations ramp up implementation of biofuels and land conservation, it is important to understand what impact these efforts have on the economy as well as the environment under different future conditions. Several studies have assessed the environmental impacts from scenarios designed to meet sustainable development objectives. Tallis et al. (2018) model a scenario that meets many sustainable development objectives, including the 50% land protection target (Tallis et al., 2018), however, their study does not consider socioeconomic or technological uncertainty nor the effects of climate change on crop yields. Additionally, van Vuuren et al. (2015) find different pathways to meet several of the Sustainable Development Goals (SDGs) and calculate their impacts on multiple environmental metrics (van Vuuren et al., 2015) though do not perform an uncertainty analysis.

This study develops a scenario ensemble to find the key multisector drivers of land scarcity impacts. We account for uncertainties in socioeconomic, agricultural yield, and climate changes and structural uncertainty in the climate and biophysical system. The uncertainties represented in this study are deep, meaning that there is no one agreed upon probability distribution to characterize them nor a universal representation of the system in which they act (Walker et al., 2012). The characterization of future socioeconomic and climate change as deeply uncertain has been well-established (Hallegatte et al., 2012; Lempert et al., 2003; Maier et al., 2016). The integrated nature of these deeply uncertain dynamics in turn renders tangential system dynamics to be deeply uncertain as well. To contend with this ambiguity, this study employs exploratory modeling to simulate possible futures throughout the represented uncertainty space. As opposed to traditional modeling approaches that aim to produce accurate predictions, the main goal of exploratory modeling is to obtain a deeper understanding of the system in question and uncover the relevant uncertainties that drive outcomes (Moallemi et al., 2020). Practitioners may then use techniques such as scenario discovery (Kwakkel & Jaxa-Rozen, 2016) to elucidate pathways to consequential outcomes without claiming to have the necessary understanding of the system to offer predictions.

Instead of delineating certain scenarios as consequential, this study focuses on the outcomes of land scarcity overall. In the outcome space, we focus on carbon emissions, crop prices, crop production, and water stress. To produce these impacts, we implement a land conservation constraint that increases protected land by over 30%, two biofuel constraints mandating the use of either first and second generation biofuels or only second generation biofuels, and the combinations of both conservation and biofuel constraints.

2. Methods

The impacts of land scarcity depend on a myriad of factors. The type of constraint implemented, the characteristics of the world in which the constraint acts, and the representation of the dynamics between sectors all strongly shape the observed impacts. In the following section, we will outline the scenario elements chosen to represent plausible states of the world (Section 2.1), the type of constraint(s) implemented (Section 2.2), and the chosen model of the coupled human-Earth system (Section 2.3). We will end the section with a discussion on the method used to discover the drivers of impacts (Section 2.4) as well as the metrics used to characterize the impacts themselves (Section 2.5).

2.1. Scenario Design

We develop a scenario ensemble to represent the deep uncertainty present in socioeconomic and environmental influences on the land-use economy. To model uncertainty in socioeconomic change, we use GCAM's implementation of the Shared Socioeconomic Pathways (SSPs, Calvin et al., 2017; O'Neill et al., 2017). The SSPs contain assumptions regarding population, wealth distribution, energy costs, food preferences, and agricultural yields, among others. The five SSPs correspond to the combinations of high and low challenges to adaptation and mitigation of climate change, with one lying in the middle of this challenge plane (SSP 2). SSP 1 is the sustainable or 'green' scenario, with low challenges to adaptation and mitigation. In this scenario, population peaks mid-century and decreases until reaching around 7 billion by 2100. People are relatively wealthy and rely on renewable sources of energy. On the opposite end of the challenge plane, SSP 3 envisions high and continued population growth with the lowest GDP per capita of all SSPs. Food demands are high, but regions do not have the technological capacity to substantially improve agricultural yields. In SSP 4, most of the world is still relatively poor, but wealth is fragmented such that there are distinct groups in the population. Finally, SSP 5 envisions a wealthy world, but this wealth is obtained by relying heavily on fossil fuels. To assess the impacts of socioeconomics and agricultural productivity specifically, we disaggregated those components along the extremes of the SSP challenge plane (i.e., SSP 1 and 3) so that some scenarios combine different elements of each (e.g., SSP 1 socioeconomics combined with SSP 3 agricultural productivity). This hybridization thus yields three scenarios in SSPs 1 and 3 for every combination of additional variables (e.g., the canonical SSP, the canonical SSP with altered socioeconomic assumptions, and the canonical SSP with altered agricultural assumptions) where the remaining SSPs only have one (see Figure 1).

It is possible to reach several different forcing levels with each SSP. We use the Representative Concentration Pathways (RCPs) to model uncertainty in climatic forcing (van Vuuren et al., 2011). Specifically, this study uses the SSP-RCP combinations modeled in CMIP5 with RCPs 2.6, 4.5, 6.0, and 8.5 (Taylor et al., 2012). We

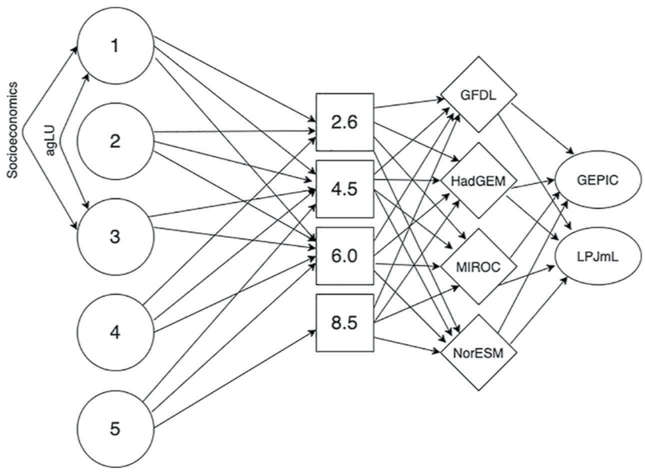

Figure 1. Schematic of the scenario design. Shared socioeconomic pathways (SSPs) are represented as circles, representative concentration pathways (RCPs) by squares, Earth System Models (ESMs) by diamonds, and crop models by ovals. Connections (224 in total) show all possible combinations.

vary carbon prices dynamically in time to ensure our modeled forcing levels are consistent with the RCP through GCAM's target finding functionality. Not every SSP-RCP combination is possible, therefore some SSPs have more combinations than others (see Figure 1).

The evolution of the climate system is also deeply uncertain (Hallegatte et al., 2012). While the main physical mechanisms are well understood, there is substantial uncertainty in climate feedbacks (Bradford et al., 2016; Lombardozzi et al., 2015) which prompts non-negligible differences in output variables between climate models (Arora et al., 2013). We represent this uncertainty by including archived CMIP5 outputs from four Earth System Models (ESMs) in the scenario ensemble: GFDL (Donner et al., 2011), HadGEM (Collins et al., 2011), IPSL (Marti et al., 2005), and NorESM (Bentsen et al., 2013).

Finally, we use available archives from two different crop models of global gridded crop yield time series to evaluate uncertainty in biophysical processes under temperature and water stresses. One model, GEPIC (Liu et al., 2007), restricts Nitrogen availability while the LPJmL model (Lapola et al., 2009) does not. Importantly, the GEPIC and LPJmL models do not capture the entire agricultural yield uncertainty space within AGMIP models (Rosenzweig et al., 2013). Rather, these models were chosen because they showed the same relative trends in yield across various crops (Calvin et al., 2020). Based on the representation of physical processes within each model, yields will be affected by changing temperatures, CO_2 concentrations, and precipitation patterns due to climate change. We calculate exogenous yield changes (excluding the endogenous changes from shifting irrigation and fertilizer) for each SSP, RCP, ESM, and crop model combination. Changes in yield will determine the degree to which the land-use economy will be impacted after implementing one of the constraints.

2.2. Land Constraints Considered

For every combination of scenario elements, the impacts of land scarcity are assessed by finding the difference between a scenario with a constraint imposed and one without, all other elements held equal. We evaluate the effects of land conservation, biofuel constraints, and the combination of the two.

To implement land conservation constraints, we change the definition of protected land in the model using the Moirai Land Data System (Di Vittorio et al., 2021; Di Vittorio et al., 2020). The land conservation constraint defines protected land as 90% of all unmanaged land while the baseline uses the protected land definitions provided by the International Union for Conservation of Nature (Ravenel & Redford, 2009) and only allows expansion into unprotected land that is deemed "suitable." Levels of suitability are derived from Zabel et al. (2014) who use membership functions of soil and climate characteristics to classify land (Zabel et al., 2014). The change in definition results in 58%–60% of total land (90% of forest and pasture) protected in the conservation scenario while under the baseline definition, only 26%–27% of land is protected (see Figure 2). Changes in areas of protected land are highly heterogeneous (see Figure 2). The regions that see the highest increases in protected area (in some cases over 60%) are those that have the highest areas of undeveloped arable land. Importantly, the land conservation constraint simulates protecting *an* additional 30% of land relative to the baseline rather than a total of 30%. Hence, the simulated constraint would only be comparable to the 30 by 30 initiative in regions that currently do not protect any of their land. However, as conservation initiatives increase in ambition (50% by 2050), higher changes in protected land may become a reality.

We implemented two biofuel constraints (first and second generation and second generation only) that are consistent with biofuel production pathways reported in the literature (Creutzig et al., 2015; Marcucci et al., 2019; Popp et al., 2014). The constraints ensure that a certain quantity of biofuel is produced and consumed globally in each timestep. The constraint begins at 64 EJ in 2025 and increases until 202 EJ in 2100 (see Figure 2). These quantities are based-off of the "High Biofuel" scenario in Wise et al. (2014) and are extrapolated until the end of the century (Wise et al., 2014). As some studies have placed the limits of sustainable biomass production at

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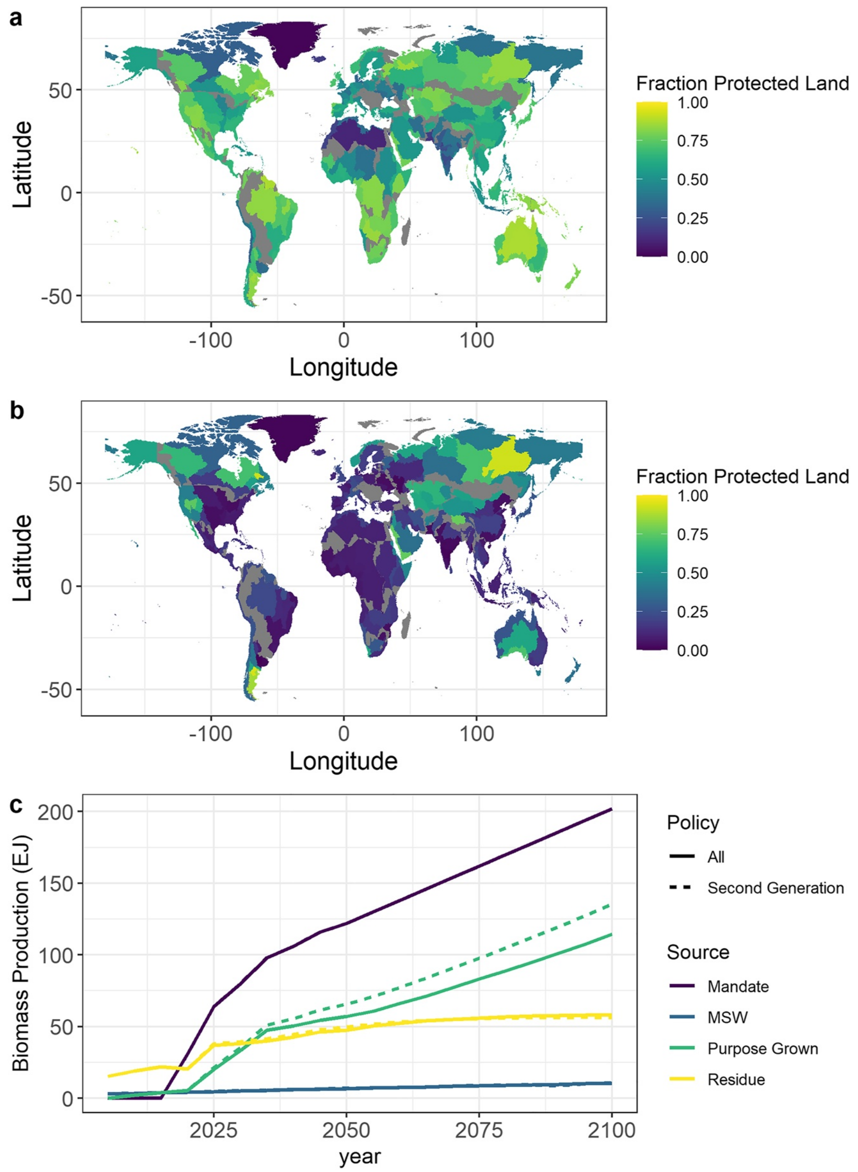

Figure 2. Protected land under the conservation constraint (a) and in the baseline (b) in each geographic land unit in the model. Missing data are represented by gray. Panel (c) depicts the biofuel mandate in both constraints and the production of different bioenergy inputs to meet the mandate. The plotted bioenergy sources do not reach the mandated amount in the All Biofuels scenario because food crops are being converted to fuel as well, though are not plotted here.

around 120 EJ/year (Searle & Malins, 2015), our constraint pathway simply represents a high yet plausible biofuel constraint to conduct a sensitivity analysis. It should not be mistaken as a projection or a policy recommendation.

In this study, first generation biofuels are derived from corn, sugar crops, oil crops, soy, and palm fruit (Wise et al., 2014). This demand is added to the total food demand for each crop. Second generation biofuels are modeled from a wide range of sources. Some nonfood crops are grown specifically for use as bioenergy including switchgrass, miscanthus, jatropha, willow, and eucalyptus. These crops are aggregated into the biomass crop class in the model. Energy is also produced from crop and forest residues and from municipal solid waste (Wise et al., 2014). Residues and wastes do not take up any additional land as they are byproducts from other uses. Importantly, the biofuel constraints were implemented on a global scale and consistently across regions. This minimizes the risk of leakage and indirect land-use change caused by conserving land (Lambin & Meyfroidt, 2011).

In total, we modeled the land conservation constraint, the first and second generation biofuel constraint, the second generation only biofuel constraint, land conservation with the first and second generation biofuel constraint, and land conservation with the second generation biofuel constraint.

2.3. Model

This study uses the Global Change Analysis Model (GCAM) 5.4, a dynamic recursive partial equilibrium model that has been used extensively in past climate assessment reports (Calvin et al., 2019; Krey et al., 2014). GCAM couples the land use, energy, hydrologic, climate, and economic systems to simulate global changes until the end of the century. GCAM splits the world into 32 geopolitical regions, 235 water basins, and 384 global land units (the intersection of geopolitical regions and water basins). Equilibrium prices for various goods and services in each region are solved for in 5 year timesteps to the end of the century. Demands (e.g., for energy, water, or food) are endogenous and depend on population, GDP, preferences, and price. The use of specific technologies (e.g., electricity from coal vs. solar) is calculated based on a logit-based choice model and depends on the relative cost or profit of the competing technologies (Calvin et al., 2019). Logit coefficients and exponents are calibrated to a historical base year of 2010 to match historical demands.

The same approach is used to allocate land types. The logit coefficients reflect the ease/difficulty of transitioning to a different land use. For instance, it is much easier to transition among agricultural crops (e.g., wheat to corn) than between commercial and noncommercial uses (e.g., wheat to protected grassland). These allocations only occur in arable land. Non-arable land types (e.g., tundra, desert, urban) cannot be expanded into and are constant through time. To increase agricultural production, more agricultural land can be allocated or existing agricultural land can be intensified. Intensification occurs by either transitioning from rainfed to irrigated land, by increased use of fertilizers, or by a combination of the two (Calvin et al., 2019). Fertilizer increases yields by around 50% and irrigation can more than double yields or have no effect on yields depending on the crop type. Agricultural yields also change exogenously through changes in technology and climate. Initial yields are based on data from Moirai, which relies on input data from the FAO, GTAP, MIRCA, and HYDE (Di Vittorio et al., 2021; Di Vittorio et al., 2020). GCAM aggregates all commodities into 15 classes: wheat, corn, rice, sugar crop, palm fruit, other grain, oil crop, miscellaneous crop, fiber crop, root tuber, biomass, forest, pasture, fodder herb, and fodder grass. The forest and pasture classes have "protected" and "unmanaged" counterparts and the shrubland and grassland classes also have "protected" counterparts where protected land cannot be converted to other land types.

2.4. Exploratory Modeling

In complex systems such as the land use system, it is difficult to anticipate what system components will drive outcomes and how the components will interact to amplify or dampen impacts. When studying such systems, researchers can simulate over many plausible future eventualities to capture the range of impacts and the relative importance of each component (Lempert et al., 2008). This exploratory modeling approach weights all scenarios equally and avoids statements of likelihood so as to not assume more knowledge of system dynamics than is appropriate in systems subject to deep uncertainty (Dolan et al., 2021; Lamontagne et al., 2018; Rozenberg et al., 2014). Using this approach, we generate scenarios using all possible combinations of factors discussed in the Scenario Design section to find the drivers of impact (i.e., the number of possible paths in Figure 1) for each of the constraints or combination of constraints implemented.

To discover driving factors of impact in the land sector, we calculate the variance explained by each factor by performing an analysis of variance (ANOVA) (Girden, 1992) for each combination of metric and constraint and finding the fraction of the sum of squares contributed by each variable out of the total sum of squares. An additional ANOVA was performed using the constraint type as a variable in the model to uncover the influence of the constraints on the impacts. By calculating the variance explained, we can uncover the relative influence of each variable on the outcome. From a decision-maker's viewpoint, some variables are more manageable than others; for instance, while decision-makers can decide to share agricultural productivity advances across regions, climate feedbacks cannot be controlled, even if they were fully understood. Recognizing significant factors and their respective ease of manipulation may help decision-makers construct impactful constraints that are robust to the uncertainty that will most determine the success of objectives. If this is not possible with the results of the analysis, uncovering influential variables sheds light on where further research is needed.

2.5. Metrics Considered

Changes in the land sector reverberate across sectors and regions. These multisector dynamics imply that a change implemented in one sector may have unanticipated detrimental or beneficial effects in others. This study therefore considers multiple metrics spanning environmental and economic objectives to capture potential tradeoffs or synergies between objectives. The economic metrics considered include changes in crop production and crop prices.

Changes in crop prices and production offer an intuitive explanation of economic impact: price increases benefit producers but injure consumers while increases in production are beneficial to all parties. Changes in production differ across crop types for the same relative price increase. Production of staple crops such as wheat and corn is more stable than other non-staple crops that have a higher price elasticity of demand. The combination of changes in price and production (i.e., change in price multiplied by change in quantity) is the revenue lost or gained from implementing the constraints.

The environmental metrics analyzed include changes in water withdrawals and carbon emissions. Increasing socioeconomic demands coupled with changing supply due to climate change will exacerbate water scarcity across the world (Vorosmarty et al., 2005). Thus, it is important to consider the water use implications of constraining land. Likewise, there is an ever-dwindling carbon budget for climate tipping points and it is therefore imperative to consider the direct and indirect emissions of land use scenarios. We therefore differentiate between emissions from fossil fuel and industrial sources (FFI) and emissions from land use change (LUC). All metrics are computed by subtracting the baseline quantity in a scenario from the quantity of its corresponding constraint scenario with all other factors (e.g., crop model, socioeconomic scenario) held equal.

3. Results

Before interpreting the results, it is important to note that the scenarios are intended to be illustrative and span a wide range of potential outcomes to aid interpretation of uncertainty across different variables. Indeed, the land conservation constraint conserves an average of around 30% additional land meaning that some regions (including heavy agricultural producers like Brazil) conserve far more (see Figure 2). The biofuel constraint, though in the range of technical and economic potential, is still high by present day standards. Thus, though we present numerical results, the values should be evaluated in relative terms compared to those of other constraints and will largely be reported as such.

In line with the objectives of the study, the first section (Section 3.1) of the results will describe the impacts of the constraints across the metrics included in the study, the next section (Section 3.2) will discuss the drivers of the observed impacts, and the final section (Section 3.3) will outline the tradeoffs and synergies between them.

3.1. Impacts of Land Constraints

3.1.1. Land Conservation

The land conservation constraint resulted in the largest increases in crop prices and the largest decreases in crop production out of the single constraints across the scenario ensemble (see Figures 3 and 5). The order of magnitude difference in price increases between the land conservation and biofuel constraints can largely be explained by the disparity in the amount of land use change induced by both kinds of constraints (see Figure 4). Around 44 million square kilometers of land is protected under the conservation constraint while only 2–3 million square kilometers of land is converted to produce biomass under the biofuel mandates. Under the land conservation constraint, up to 2 million square kilometers of cropland is converted per year while the biofuel constraints remove up to only 550,000 square kilometers of cropland. This large reduction in the supply of available cropland drives the high crop price increases and production decreases under the land conservation constraint. Out of the scenarios under the land conservation constraint, SSP 3 scenarios produced on average both the highest magnitudes and the highest variability in the economic metrics (see Figures 3 and 5). The large magnitudes occur because high food demands from high population lead to steep price increases while low productivity leads to high production losses when land is constrained. The combination of high population and low productivity in SSP 3 renders the food system more sensitive to hydroclimatic variability, thus producing a wide range of outcomes across the other dimensions of the scenario ensemble.

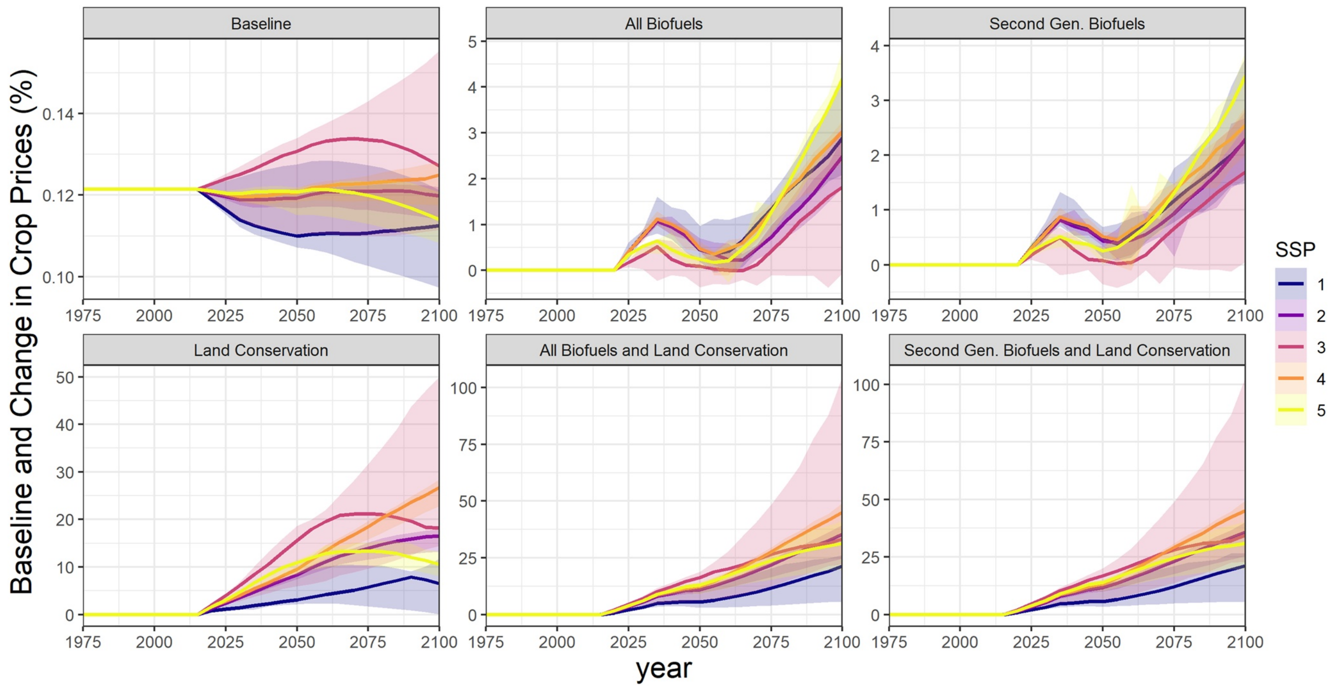

Figure 3. The percent change in the price of food crops due to implementing the constraints averaged across crop types and regions through time. The top left panel shows the baseline prices (i.e., with no constraint imposed) averaged across regions and crop types in $/kg. Colors indicate the shared socioeconomic pathway (SSP) scenario. The solid lines depict the median within the SSP group while the transparent ribbons show the range over all scenarios within the SSP group.

Even among high impact scenarios, regions experienced highly variable price changes in food commodities. Much of this heterogeneity can be explained by the varying conservation constraints imposed across regions (see Figure 2), although normalizing by change in protected area reveals heterogeneous impacts as well (see Figure S1 in Supporting Information S1). Poorer nations are disproportionately affected by land conservation. This effect is demonstrated by the inverse relationship between GDP and percent change in price in Figure 6 in the land conservation policies. When normalized by protected area, average crop prices can increase by over 6% in India and Pakistan while prices barely change or even decrease in the USA (see Figure S1 in Supporting Information S1). This occurs because when wealthier countries import food, prices barely increase or go down compared to domestic prices but increase in poorer countries. The regional differences are exacerbated by the representation of how land is conserved in this study. Developing regions typically have higher amounts of unmanaged land and thus more land is protected using the changed definitions of protected areas. The regional differences in impact underscore the importance of considering regional socioeconomic contexts in deeply uncertain conditions before making land use decisions. Globally, crop prices increased on average around 15% by the end of the century and up to 50% in SSP 3 scenarios (see Figure 3). Because of the low price elasticity of demand of food commodities in GCAM, the relative decreases in production are considerably lower than their corresponding price increases across the scenario ensemble (see Figure 5).

While all regions experience negative economic outcomes from land conservation, the environmental outcomes are mixed across regions. Water withdrawals increase on average under the land conservation constraint but decrease in some regions when agricultural production declines (see Figure 7). Even though production decreases in the majority of regions, water withdrawals increase because producers are forced to intensify their yields when agricultural land is constrained. To accomplish this, producers switch from rainfed agriculture to irrigated agriculture, thus prompting water withdrawals. When normalized by renewable supply, the impact of land conservation is more apparent. Land conservation increases the Water Stress Index (WSI; water withdrawals over renewable supply) by over 0.2 in several regions (see Figure 8). Regions are typically considered water stressed if they have a WSI above 0.4 (Vorosmarty et al., 2005), thus increases of this magnitude are substantial. Land conservation also yields mixed impacts in terms of carbon emissions. Potential emissions from land use change are averted when land is conserved in its undeveloped state. Conversely, when land is constrained, the price of

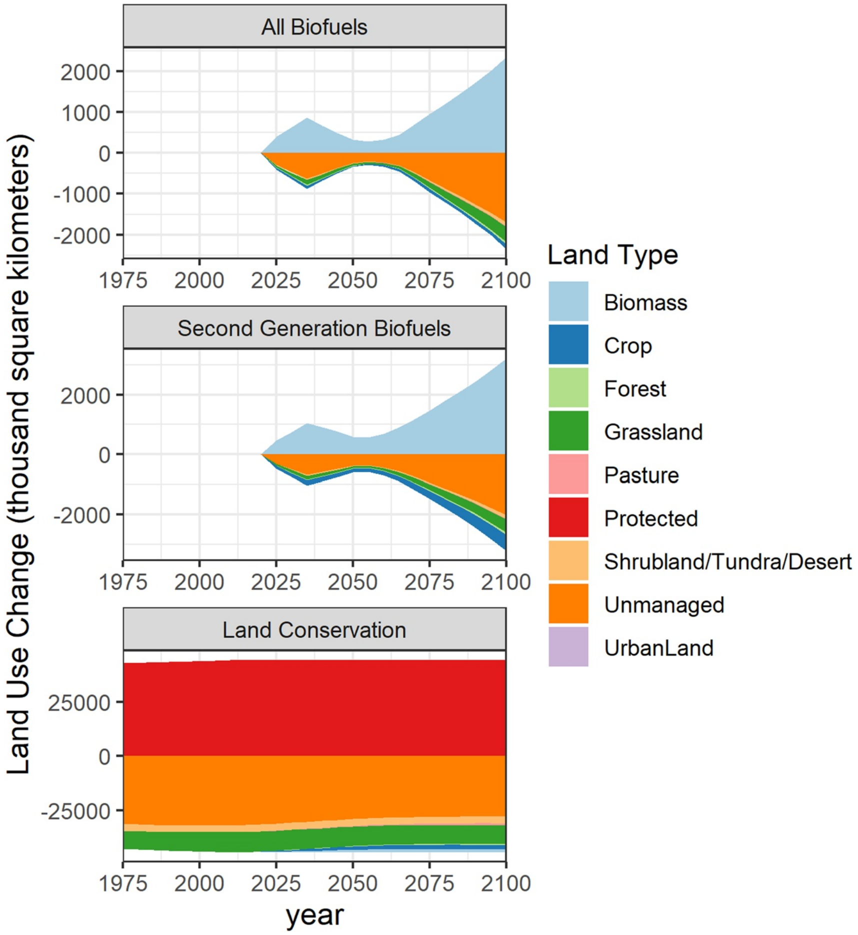

Figure 4. The amount of global land use change over the century due to imposing each of the single constraints in thousands of kilometers squared. Land types are represented by colors. Values are averaged across the scenario ensemble.

biomass increases and prompts the transition from biofuels to oil. This results in higher emissions from FFI sources (red in Figure 9). Overall however, the savings from land use change outweigh the increased FFI emissions to yield net emission reductions from land conservation.

3.1.2. Biofuels

The biofuel constraints on the whole produce lower magnitude economic impacts but similar environmental impacts compared to those under the land conservation constraint. Changes in average crop price are similar between the combined biofuel and second generation biofuel constraints at a maximum of 5% by the end of the century. However, the two constraints produce diverse effects on crop production. While agricultural production decreases under the second generation constraint, it increases by a higher magnitude under the combined biofuel constraint (see Figure 5). Because the combined biofuel constraint includes food products that are used for energy (i.e., first generation fuels), the mandated production prompts increases in the production of those crops. Meanwhile, the second generation constraint reduces the production of first generation crops because the mandated energy consumption excludes those crops in favor of biomass.

The increased production of biomass and other food crops prompts increases in water withdrawals (see Figure 7). Both constraints produce similar changes in regional WSI (see Figure 8) despite differences in their agricultural production. The production increases occur largely in regions with relatively higher amounts of runoff (e.g., Brazil) and thus the differences in the WSI are minimal. Changes in carbon emissions are also similar between the two constraints. In the median SSP scenarios (i.e., the lines in Figure S2 in Supporting Information S1), the emission reductions range from 0.5 to 1 GtC. Both biofuel constraints produce net positive LUC emissions from converting unmanaged land to biomass production, but save a higher magnitude of FFI emissions to generate net

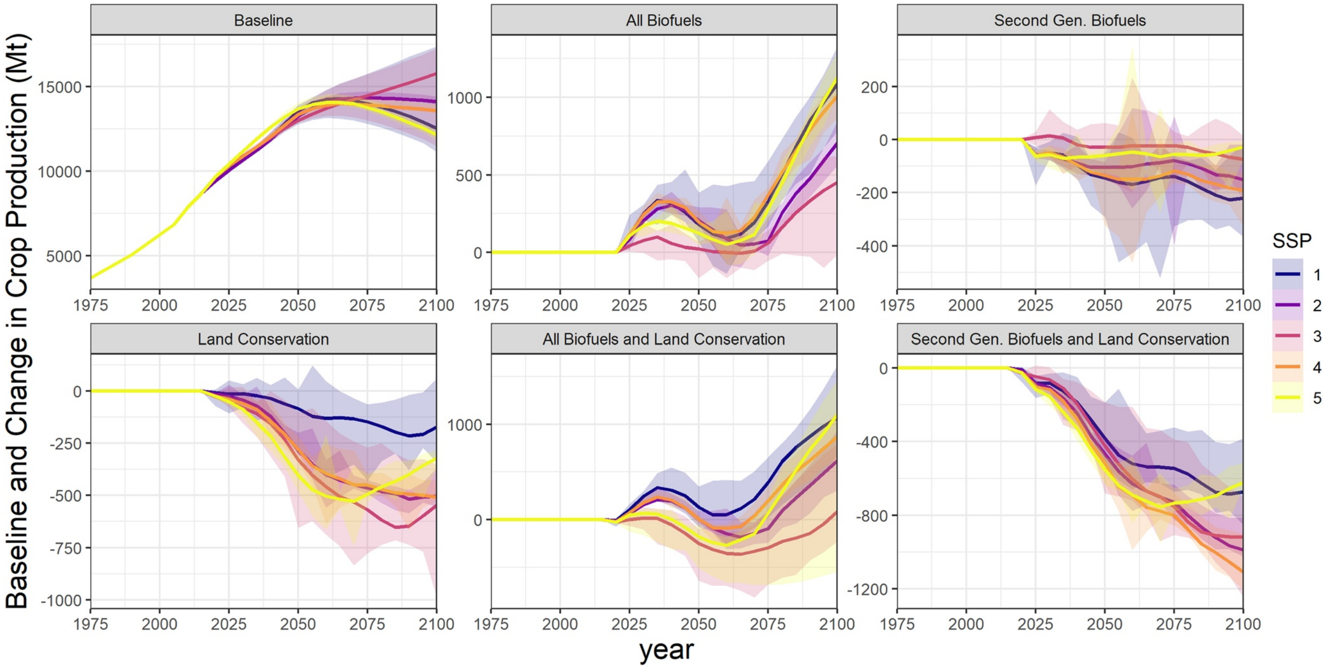

Figure 5. The change in total food production (sum of all crop types for all regions) through time in Mt. The interpretation of the colors, ribbons, and orientation of the panels is the same as in Figure 3.

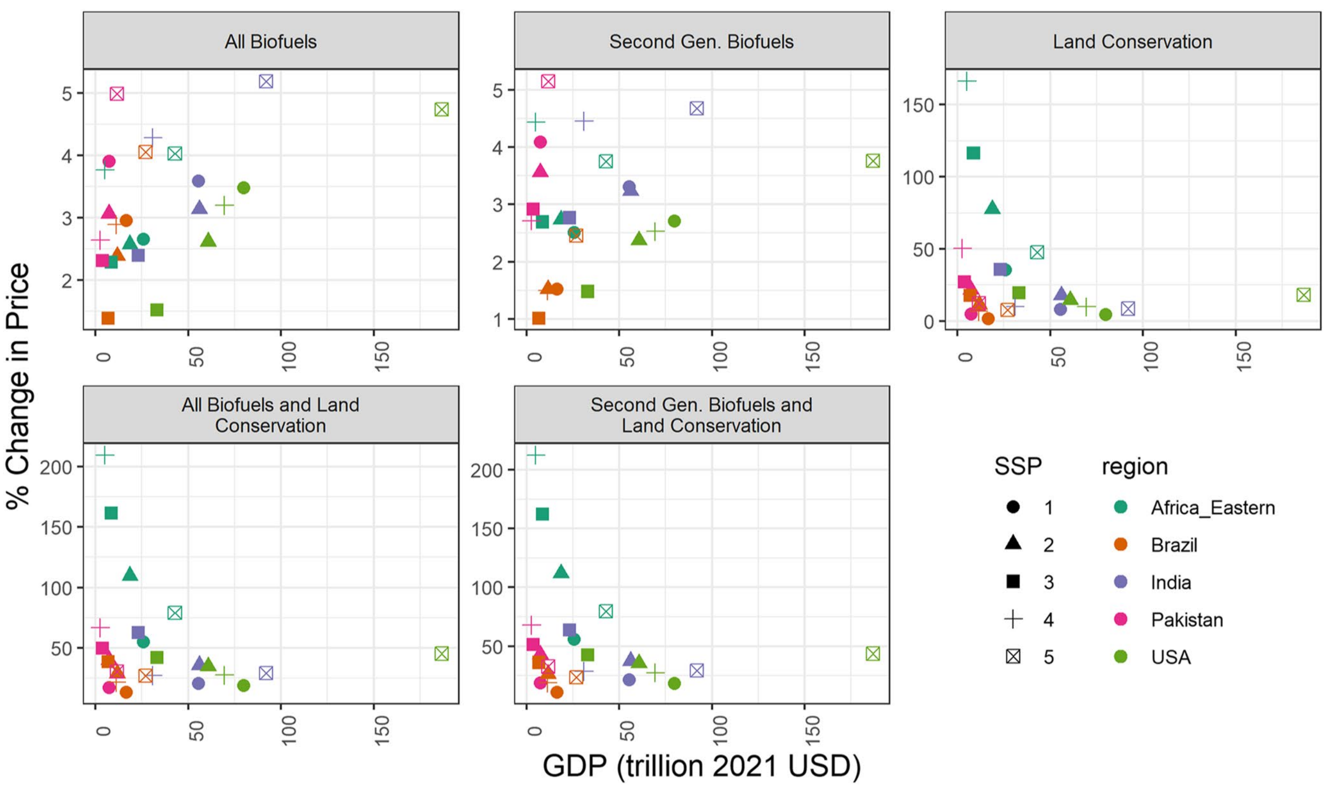

Figure 6. Average change in crop price across crop commodities plotted against regional GDP in 2100. Values are averaged across crop model, representative concentration pathway (RCP), and Earth System Model (ESM). Colors depict different regions and shapes depict shared socioeconomic pathways (SSPs).

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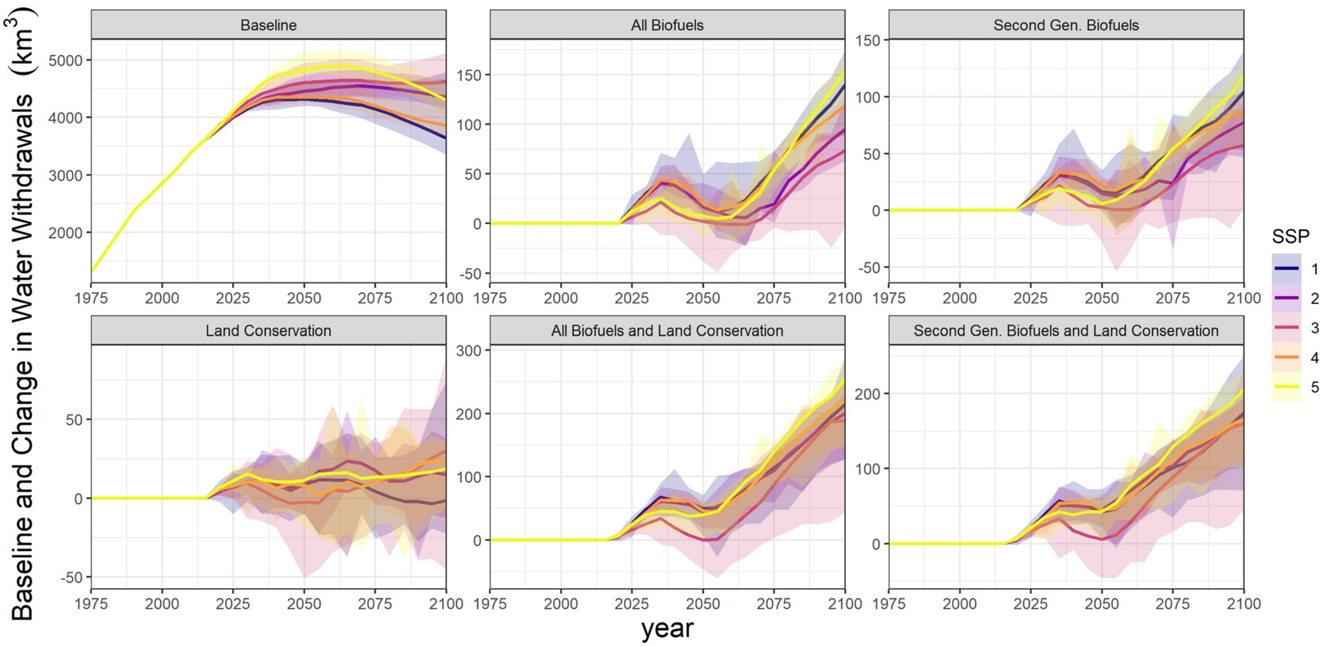

Figure 7. Change in total water withdrawals (sum of all regions) through time in cubic kilometers. The interpretation of the colors, ribbons, and orientation of the panels is the same as in Figure 3.

negative emissions overall (as shown by the purple lines in Figure 9 and by all lines in Figure S2 in Supporting Information S1).

3.1.3. Joint Constraints

Across the scenario ensemble, the joint constraints amplify the impacts of single constraints when both single constraints are acting in the same direction. For instance, if the single constraints both increase some metric, their combination results in a larger increase than either of the single constraints. While this result is intuitive in itself, the resulting magnitude of the amplification of impact in some metrics is notable. For example, the amplification effect is demonstrated clearly by change in agricultural prices under the joint constraints. Average crop prices can increase up to 100% in SSP 3 scenarios under the joint constraints as opposed to 50% and 5% under the single land conservation and biofuel constraints respectively (see Figure 3). When the single constraints generate impacts in opposite directions, the impacts under the joint constraints are dampened relative to the single constraints. For example, production under the joint land conservation and combined biofuel constraint does not fall as much as it would under land conservation alone (see Figure 5). Both the amplification and dampening mechanisms may be favorable or detrimental depending on the desired effect but need to be considered in the context of the effects on other metrics as well.

3.2. Sensitivity Analysis

Land scarcity impacts varied substantially depending on the constraint implemented. Indeed, ANOVA sensitivity analysis of the included variables showed that the type of constraint implemented held the most explanatory power out of all dimensions varied in the experiment (see Figure 10). This result signifies that the magnitude and direction of impacts are largely controllable. Within a single constraint, SSP assumptions (excluding agriculture and socioeconomic components) were the most influential variable in almost every metric assessed.

The agricultural dimension of the SSPs explained very little of the variance in outcomes under the biofuel constraint but was significant in driving crop prices in scenarios that implemented land conservation. Meanwhile, the socioeconomic dimension of the SSPs stands out as explaining a high proportion of the variance in the outcomes in most metrics under the biofuel constraints and water withdrawals in land conservation scenarios (see Figure 10). The combination of the agricultural and socioeconomic components of the SSPs did not explain a

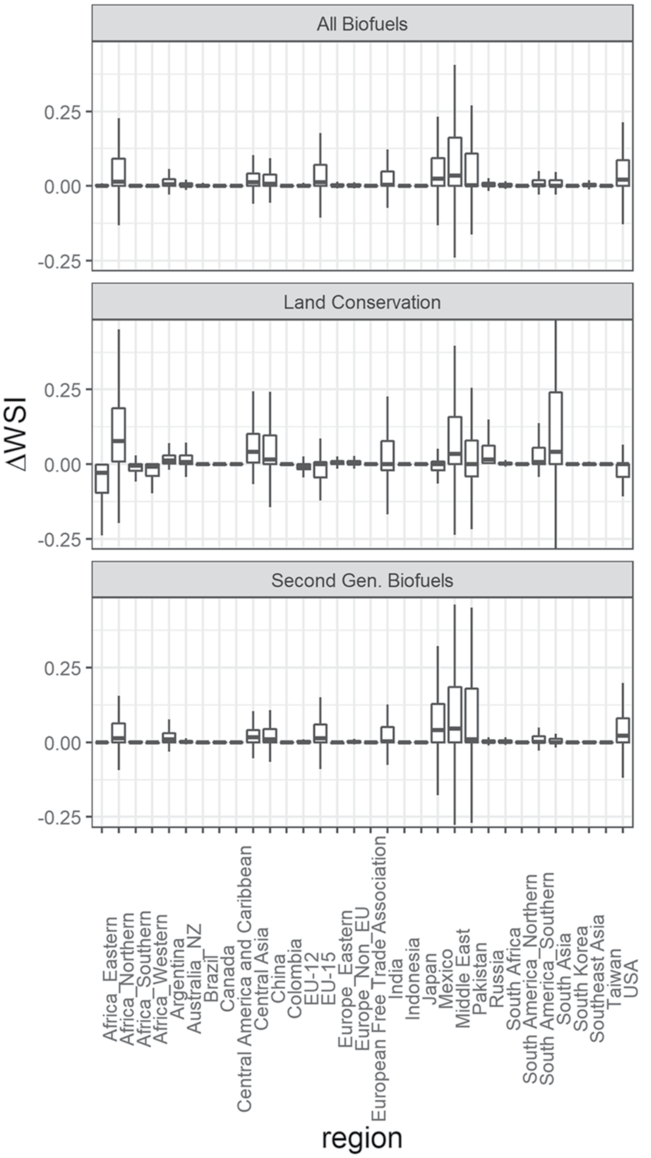

Figure 8. Boxplots of the change in Water Stress Index (WSI), or withdrawals over renewable supply, in each region with the addition of a single constraint. The midline of the boxplots depict the median and the lower and upper hinges depict the 25th and 75th percentiles, respectively. The whiskers are plotted to a distance of 1.5 times the inter-quartile range.

high proportion of the variance within the SSPs in most scenarios. Therefore, further work should disaggregate other SSP components to assess their relative influence over land scarcity impacts.

Notably, the RCP, ESM, and crop model variables had comparatively negligible explanatory power over the outcomes. In this study, anthropogenic uncertainties were the main drivers determining the impacts of the land constraints. Future work could expand the number of climate scenarios and crop models to test the robustness of these results.

3.3. Tradeoffs and Synergies

Considering the potential tradeoffs between metrics helps to guard against unanticipated consequences that may have occurred if considering a single objective (Giuliani et al., 2014). Fortunately, multi-metric analysis has been gaining traction in the policy sphere in recent years, most notably with the implementation and measurement of the Sustainable Development Goals (SDGs) (Colglazier, 2015; Fullman et al., 2017; Huan et al., 2021) and the recent success of the "donut" model of the economy (Golias, 2019; Meredith, 2021; Raworth, 2017; Yamaguchi et al., 2020). Both the SDGs and the donut model balance environmental and social objectives to ensure stable ecosystems and equitable communities. While this study does not consider equality as a metric in itself, we address heterogeneous impacts by assessing tradeoffs and synergies at the regional scale.

The relationships between metrics are relatively consistent across the scenario ensemble under the single constraints. Among the relationships between metrics, one of the clearest tradeoffs is between crop production and water withdrawals, where higher increases in crop production yield higher water withdrawals. Favorable conditions (e.g., lower water withdrawals, lower prices, higher production) are plotted as positive values in Figure 11 and thus tradeoffs can be seen wherever the values change sign. The severity of the tradeoff is shown by the vertical axis where the values are the log modulus of the percent change in a metric. The log modulus is given by $L = \text{sign}(x) * \log(|x| + 1)$ so that a value of -1 would correspond to a loss of 10%. For example, in the land conservation scenarios, water withdrawals in Eastern Africa decrease by 10% although average crop prices increase around 50% and production decreases by 16%. Some relationships between metrics are synergistic, such as between carbon emissions and agricultural production under the biofuel constraints. Even though the added production increases LUC emissions when land is converted from forest to biomass, there is a higher magnitude of FFI emission reductions so that carbon emissions are reduced overall. The relationship between carbon emissions and water withdrawals is dependent on the region and on the constraint implemented. Producing more biofuels necessarily increases water consumption (forcing a tradeoff), though land conservation yields substantial water savings and carbon mitigation in certain regions because less land is under production (allowing a synergy). On the global scale, however, land conservation leads to increased irrigation and thus increased water withdrawals overall.

The biofuel constraints yield less variability between regions compared to the land conservation constraint. The only noticeable outlier between regions is carbon emission mitigation in Brazil (shown in orange), which increases under the combined biofuel constraint and falls under the second generation constraint. Brazil's production in Mt of sugar crops (a first generation biofuel crop) in the baseline is higher than any other region's output of a single crop, and therefore Brazil is able to meet the biofuel mandate under the combined biofuel constraint with the existing sugar crop production. However, under the second generation biofuel constraint, Brazil must switch to biomass production from sugar crops and thus produce LUC emissions. The biofuel constraints show relatively

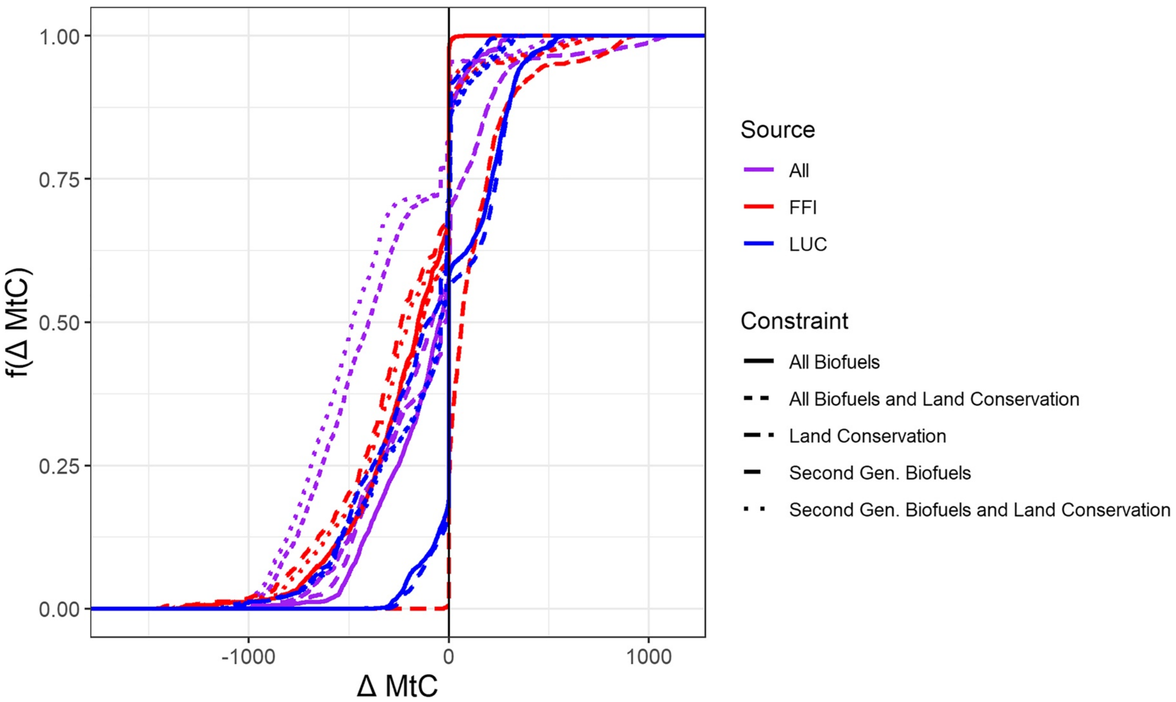

Figure 9. Empirical cumulative distribution function of changes in global carbon emissions in megatonnes (Mt) from implementing a single constraint for every scenario-year combination. Colors represent the source of the emissions while linetypes specify the constraint.

low levels of uncertainty in the different metrics across SSPs compared to land conservation and the joint constraints. Among the land conservation and joint constraints, African regions stand out as exhibiting the strongest tradeoffs between metrics. The joint constraints amplify the tradeoffs exhibited in land conservation scenarios.

4. Discussion/Conclusions

It has long been understood that land is a necessary component to economic development, and that its proper management is paramount for sustained growth (Barbier, 2003). Many different uses compete for a limited amount of land, and converting to one use type may permanently preclude using it for other purposes in the future (e.g., conversion from old growth forest to agriculture). Agricultural development, logging, or other commercial purposes for land could compete with conservation-based practices implemented solely for mitigation purposes or to maintain biodiversity and stable ecosystems. This multimetric problem is complicated by the vast amount of uncertainties that impact land and land use and the complex relationships between affected sectors. In this respect, land management is an inherently wicked problem (Rittel & Webber, 1973) in that objectives differ across stakeholder groups, the system or the problem formulation itself is in a constant state of flux, decisions may ultimately be irreversible, and improvements in one sector may result in degradation in another. In such a problem, there may be no right answer but there are severe consequences for getting it wrong (Rittel & Webber, 1973). How then, does one address the wicked problem of land management? We maintain that there are several crucial elements in a land management study. To begin, the multisector dynamics of the system must be accounted for. The human and earth systems are inextricably linked, and failing to model the feedbacks between sectors will only result in a mischaracterization of the system. Many elements that drive these dynamics (e.g., technologic change) are deeply uncertain and cannot be predicted. Rather, modeling a spectrum of conceivable eventualities motivates the implementation of robust plans. Further, impacts must be measured using a range of metrics. Stakeholders may have different objectives and the complex multisector dynamics of the system often force tradeoffs between objectives. Understanding these tradeoffs and how they differ across regions helps avert the consequences of myopic decisions.

This study aimed to characterize the human-Earth system response of restricting land available for agriculture, and in doing so, illustrated the importance of these three elements. We evaluated the effects of representative

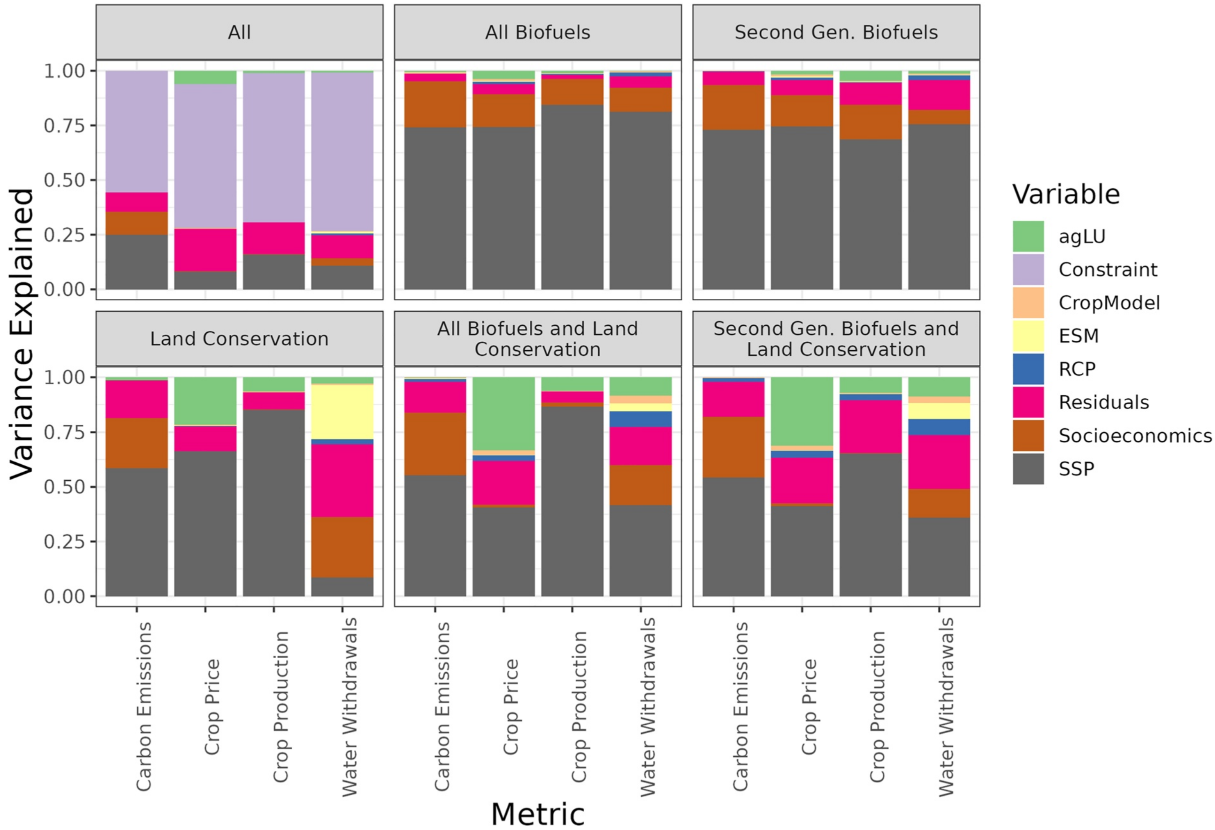

Figure 10. The variance explained by each variable (represented by colors) in the experimental design for all metrics as calculated by an analysis of variance (ANOVA) of first-order effects. The shared socioeconomic pathway (SSP) variable contains all assumptions within the SSPs except for those included in the agriculture and socioeconomic variables. The top left panel includes the constraints as a variable while the others depict the variance explained by the other variables within a constraint.

land constraints on economic and environmental metrics of interest. As the future is deeply uncertain, we simulated these constraints under a wide range of future conditions. The results of these simulations led us to three key points. First, we found that in general, land constraints have a substantial beneficial impact on reductions in carbon emissions but at the cost of increased water withdrawals and food prices, and reductions in food production. Second, these impacts may be amplified or dampened if multiple constraints are added together. Intended amplification of impacts in one sector (e.g., carbon emission reductions) may lead to amplified negative impacts in another (e.g., agricultural prices). This is an especially salient consideration in regions that are disproportionately impacted. We observe that African regions suffer the most negative impacts overall from implementing the constraints, although impacts are heavily dependent on the constraint implemented and the SSP in which they act. Third, we found that the type of constraint implemented was a greater determinant of impact than all of the uncertainties present in the ensemble. Within a constraint, the SSP assumptions held the most explanatory power of impacts in all metrics. The emission pathways, climate models and crop models had a much smaller impact than SSP assumptions on most of the metrics evaluated. This means that overall, uncertainties in the human system were far more influential than environmental uncertainties in determining environmental and economic impacts. The drivers of impact are either factors that decision-makers can control completely (i.e., the constraints) or else have at least some influence over (e.g., agricultural yield increases). This finding presents a more hopeful outlook for the future.

As with any study, these key findings come with caveats. For instance, the final result of the sensitivity of impacts to deep uncertainties is highly conditional on the experimental design. Future work is needed to test the robustness of our findings using a broader sampling of climate and biophysical uncertainty. Further, this study only assessed impacts on the land-use economy. Future work could conduct a similar exploratory impact analysis using a general equilibrium framework to assess impacts on the entire economy. Future work could also include

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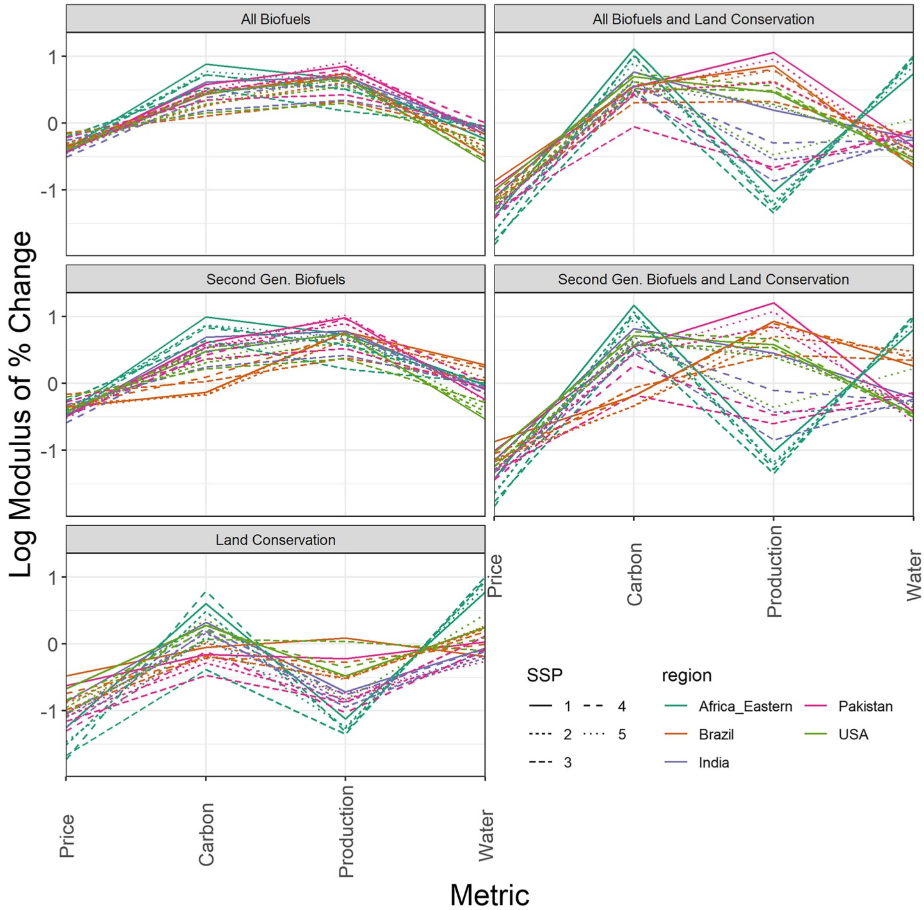

Figure 11. Tradeoffs and synergies between the economic and environmental metrics. Lines are the average across scenarios within a shared socioeconomic pathway (SSP), while SSPs are denoted by line types. Regions are represented by colors. The values depict the log modulus of percent change in the metric. Positive values are considered favorable while negative values are detrimental. Values for carbon emissions, prices, and water withdrawals are reversed so that reductions are viewed as favorable. Note that positive values are considered from the consumer standpoint. Increases in agricultural prices are plotted as not favorable yet would be favorable to producers.

the value of ecosystem services to provide a more complete view of the impact of land scarcity. Finally, while GCAM models the average consumer with an average income in a particular region, it is important to consider the distributional effects of price increases as the poor will be more heavily impacted by the same price increases than the average consumer. This shortcoming is shared by many other Integrated Assessment Models but must be resolved so that these models can more effectively help guide the path toward a more equitable and sustainable future.

Data Availability Statement

Requests for raw data should be made to flannery.dolan@tufts.edu. Processed data and code to generate the figures can be found in the (Dolan, 2021) Zenodo repository at https://zenodo.org/record/5768005#.Ye62h_7MK70.

Acknowledgments
This research was supported by the U.S. Department of Energy, Office of Science, as part of research in MultiSector Dynamics, Earth and Environmental System Modeling Program.

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