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Special Section:

Multi-Sector Dynamics:
Advancing Complex Adaptive
Human-Earth Systems Science
in a World of Interconnected
Risks

Key Points:

- Long-term implications of population and GDP changes on the coupled human-Earth system focusing on multisectoral and regional understanding
- Uncertainties in GDP and population growth can compound, resulting in more extreme outcomes for multisectoral systems
- Compounding uncertainties differ by region and metrics; staple food prices and water withdrawal show significant regional variability

Supporting Information:

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

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Compounding Uncertainties in Economic and Population Growth Increase Tail Risks for Relevant Outcomes Across Sectors

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Abstract Understanding the long-term effects of population and GDP changes requires a multisectoral and regional understanding of the coupled human-Earth system, as the long-term evolution of this coupled system is influenced by human decisions and the Earth system. This study investigates the impact of compounding economic and population growth uncertainties on long-term multisectoral outcomes. We use the Global Change Analysis Model (GCAM) to explore the influence of compounding and feedback between future GDP and population growth on four key sectors: final energy consumption, water withdrawal, staple food prices, and CO₂ emissions. The results show that uncertainties in GDP and population compound, resulting in a magnification of tail risks for outcomes across sectors and regions. Compounding uncertainties significantly impact metrics such as CO₂ emissions and final energy consumption, particularly at the upper tail at both global and regional levels. However, the impact of staple food prices and water withdrawal depends on regional factors. Additionally, an alternative low-carbon transition scenario could compound uncertainties and increase tail risk, particularly in staple food prices, highlighting the influence of emergent constraints on land availability and food-energy competition for land use. The findings underscore the importance of considering and adequately accounting for compounding uncertainties in key drivers of multisectoral systems to enhance our comprehensive understanding of the complex nature of multisectoral systems. The paper provides valuable insights into the potential implications of compounding uncertainties.

Plain Language Summary Understanding how future population and economic growth changes could impact our energy, water, food, and environment requires looking across multiple sectors and regions. This is because these systems are all connected. For example, increasing population drives higher food demand but requires more energy and water to grow food. At the same time, reducing greenhouse gas emissions from energy through increased biofuel consumption can compete with food production for land resources. This study explored how uncertainties in future population and GDP growth could compound and interact to affect future energy use, water withdrawal, staple food prices, and carbon dioxide emissions. Using a model that connects all these systems, the study found that combined uncertainties in population and GDP lead to more significant risks of extreme outcomes than individually looking at those uncertainties. There are substantial regional differences in future outcomes, like higher uncertainty in food prices for India and West Africa compared to other regions. We highlight the need to consider multisector and multisystem interactions between uncertainties across different regions. Accounting for these compounding uncertainties provides valuable insights into potential risks, like higher extreme projections for food prices or water use. These insights are essential for long-term planning in our connected human-Earth system.

1. Introduction

The future co-evolution of the human-Earth system remains highly uncertain. This uncertainty stems from the complex interplay of various uncertain drivers, such as economic and population growth, technological advancements, resource availability, and societal policies. The implications of these uncertain drivers for long-term development are significant and affect outcomes of interest across sectors and regions, suggesting the benefits of taking a multisectoral and multi-regional approach to understanding of the coupled human-Earth system (Reed et al., 2022). Multisector system representations consider dynamic and endogenous interactions between sectors

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and enable the identification and analysis of crucial uncertainties influencing systems evolution and potential tradeoffs between sectors (Dolan et al., 2021; Reed et al., 2022). Previous studies have explored different combinations of uncertain drivers and their implications for multisectoral systems, employing various approaches including but not limited to sensitivity analysis, uncertainty analysis, and exploratory modeling. According to Srikrishnan et al. (2022), uncertainty analysis is crucial in assessing risk, projecting future scenarios, and planning for complex systems in multi-sector environments. They identified critical challenges in uncertainty analysis for multi-sector dynamics and concluded that addressing it requires deliberate tradeoffs and careful consideration of interactions and feedback.

Other studies have underscored the critical importance of characterizing compounding uncertainties and the increasing risk of extreme outcomes. For example, Harrington et al. (2021) highlight challenges in transparently assessing uncertainty in simplified climate risk frameworks. They methodologically illustrate how different dimensions of uncertainty affect risk thresholds for extreme heat. Christensen et al. (2018) show how uncertainty in long-run economic growth projections affects high emissions outcomes and emphasizes the potential for more extreme climate change outcomes. Rising et al. (2022) identify the omission of “missing risks” in economic evaluations, highlighting how interconnected physical and social systems can give rise to complex and often underestimated risks. O’Neill et al. (2020) recommend incorporating narrative descriptions of low-probability, high-risk scenarios to enhance consideration of extreme outcomes. Building on this literature, this study explores the interplay of economic and population growth uncertainties within the human-Earth system, investigating how these uncertainties can compound and potentially magnify tail risks of outcomes across several key sectors, shedding light on their long-term impacts on energy, water, emissions, and land use change outcomes.

Changes in future GDP and population growth can significantly impact multisectoral outcomes; however, the relative impact of population and GDP on each metric varies depending on the specific circumstances (Abbott et al., 2008). For example, a study by the Food and Agriculture Organization (FAO, 2017) found that both population growth and economic growth were important drivers of food demand and prices. However, the relative importance of each factor varied depending on the country and region in question. They found that in some countries, population growth was the dominant driver of food demand and prices, while in others, economic growth was more important. Regional heterogeneity in the effects of population growth on GDP and the feedback between economic growth and population growth leads to heterogeneous regional demand growth (Cumming & von Cramon-Taubadel, 2018). Thus, different assumptions about the feedback between GDP and population growth could be critical in understanding alternative futures of multisectoral interactions.

It is common in the literature to perform simple sensitivity experiments on GDP and population to explore how different values for these drivers affect outcomes of interest (e.g., Headey & Hodge, 2009; Sampedro et al., 2022). However, investigation of how the representation of feedback and interactions between GDP and population affects outcomes remains a scientific gap in the literature. Many studies have explored different feedbacks and correlations between population growth and economic growth (e.g., Dao, 2012; Headey & Hodge, 2009; Peterson, 2017; Prettnner, 2014), identifying differences for developed versus developing countries. In models, the feedback from population to GDP is often captured via region-specific labor productivity factors directly influencing GDP. Our goal is not to investigate a wide variety of possible interactions between population and GDP or to identify the most appropriate feedback mechanisms to include in models. Rather, we use a simple set of four example representations of population and GDP uncertainty and their interplay with the aim of demonstrating the importance of feedback representation and how it affects results for outcomes of interest, thereby highlighting the need for these feedbacks and correlations to be more carefully considered in modeling, especially for complex systems.

In this work, we take an approach based on Morris et al. (2022) to systematically explore uncertainty in GDP and population growth under different assumptions about how the two drivers interact. This approach enables the examination of the compounding effects of these two factors. We explore the influence of the feedback and interactions between future GDP and population growth on outcomes in four key sectors, namely final energy consumption, water withdrawal, staple crop prices (which includes rice, wheat, corn, roots and tubers, and other staple grains), and CO₂ emissions, using the Global Change Analysis Model (GCAM) version 6. How uncertainty in GDP and population growth is incorporated is particularly important in understanding results from an integrated, multisectoral model as the inherent connections between sectors allow uncertainty to propagate. For example, in GCAM, water withdrawal is influenced by the uncertain GDP and population drivers as well as

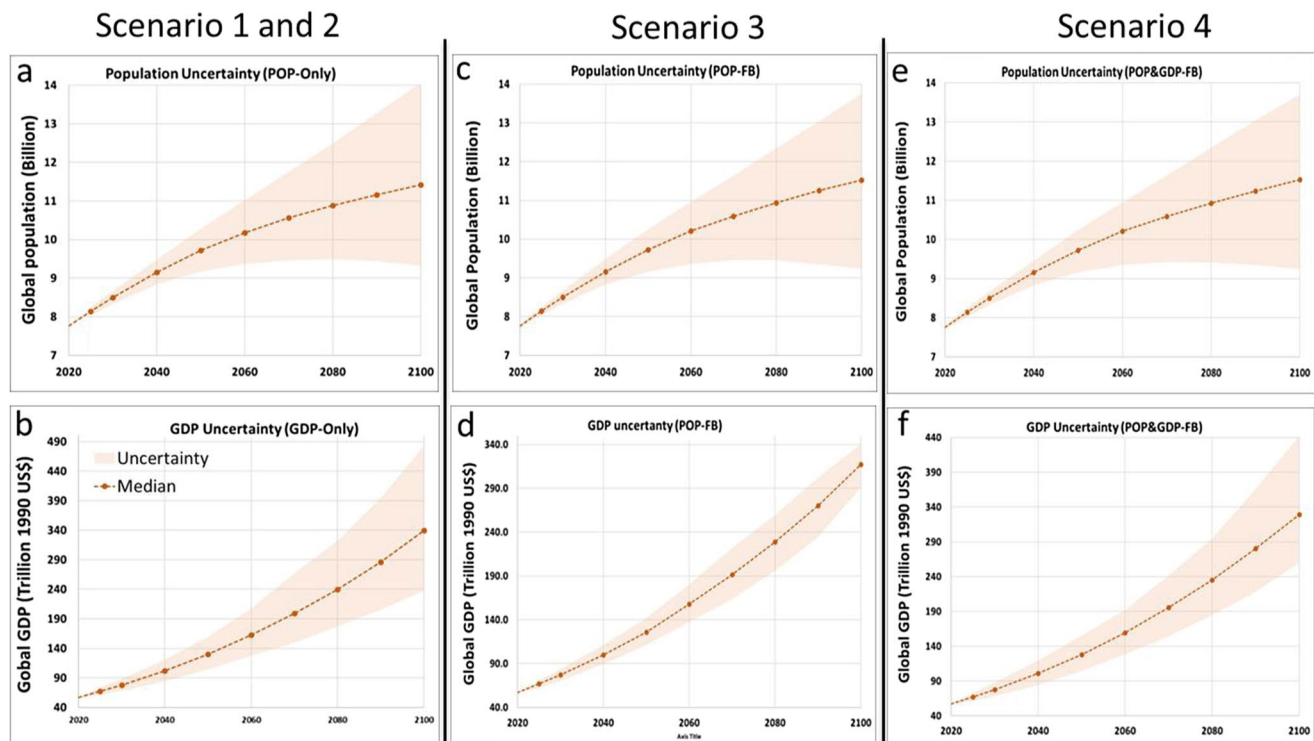


Figure 1. Distributions of Global Population and GDP Uncertainty. Scenario (1) & (2): Global population and GDP Uncertainty only scenarios respectively. Scenario (3): Global population with feedback to GDP (POP-FB). Scenario (4): Combined population and GDP uncertainty with feedback (POP&GDP-FB). The shaded area represents the range between the fifth to the 95th percentile for each distribution.

dynamics in the land and energy sectors, which are also driven by the main uncertain drivers. Moreover, the integrated nature of GCAM allows evaluation of the robustness of our core findings across fundamentally different regimes of behavior. We find that for many sectors, the uncertainties in GDP and population compound resulting in a magnification of tail risks for outcomes across sectors. The following section describes the population and GDP scenarios, followed by an introduction of the model (GCAM), and finally the results and implications of this study.

2. Methods

2.1. Population and GDP Growth Uncertainties

How uncertainty and feedback between population and GDP are represented is an important consideration in integrated, multisector models. Here we develop large ensembles of 1,000 samples for each of four scenarios representing different methods of incorporating these uncertainties and their interactions.

1. Population uncertainty only: Pop-Only
2. GDP uncertainty only: GDP-Only
3. Population uncertainty with feedback to GDP: POP-FB
4. Both GDP and population uncertainty, with feedback from population to GDP: POP&GDP-FB

The GDP and population ensembles drawn in each scenario are summarized at the global level in Figure 1. As described below, regional heterogeneity exists in each ensemble. Scenarios (1) and (2) vary population or GDP alone and can be used for sensitivity analysis, while scenarios (3) and (4) represent two different methods for accounting for the observed historical feedback and correlation between population and GDP.

In the GDP-Only scenario, GDP growth is represented as uncertain (Figure 1, panel b shows the resulting total GDP), while the population trajectory is held at the median of the Pop-Only distribution (Figure 1a). Uncertainty in GDP growth is derived following Morris et al. (2022) from a random walk with drift that uses re-sampled

historical regional GDP volatility as random shocks, with distributions constructed for each GCAM region (See Table S1 in Supporting Information S1 for all region specific values). The drift term (mean) in the random walk procedure is based on reference growth rate projections for each region, which reflect the current judgments of long-term growth for each region (IEA, 2018; IMF, 2018). In contrast, in the second scenario (POP-Only, Figure 1, panel a), population uncertainty for each GCAM region is derived from country-level probabilistic projections from the United Nations (UN, 2016) while GDP growth is held at the median trajectory of the GDP-Only distribution.

In reality, there are feedbacks between population and GDP growth. Here we focus on the impacts of population on GDP. Scenario three (POP-FB, Figure 1, middle column, panels c and d) captures population uncertainty with a simple representation of the feedback between population and GDP growth, which in the model is mediated through the labor productivity growth rate. As in scenario two, population uncertainty is derived from country-level probabilistic projections from the United Nations (UN, 2016). However, here, a correlation between population and GDP growth rates is incorporated when performing the draws from the GDP and population distributions, with the correlation coefficient calculated based on the endogenous GDP response to the population uncertainty from the model employed in Morris et al. (2022), which allows GDP to respond endogenously to changing populations. In this case, the global population and GDP growth rates have a Pearson's correlation coefficient of 0.78. The final scenario (POP&GDP-FB, Figure 1, right column, panels e and f) captures uncertainty in both GDP and population growth together, while also representing feedback between the two. In this scenario, the uncertainty in GDP growth has an offsetting effect on the population uncertainty, so the resulting relationship between GDP and population is characterized by a weaker correlation coefficient. Therefore, correlated draws for GDP and population are performed with a Pearson's correlation coefficient between population and GDP growth rates of 0.38 (based on the model employed in Morris et al. (2022)). This scenario reflects how these uncertainties both interact and compound over time.

Comparing results from scenarios (1) and (2) can capture the impact of isolated uncertainties, including the strength of the GDP impact versus the population impact, but cannot account for the compounding effects of GDP and population uncertainties. Comparing results from scenario (2) with those from scenarios (3) or (4) can assess the impact of including feedback between population and GDP in different ways. Comparing results from scenarios (3) and (4) allows for examining the effects of compounding uncertainties (e.g., how results change when both GDP and population growth are uncertain at the same time). The four scenarios are simulated with the Global Change Analysis Model (GCAM) (Calvin et al., 2019), which models the multisector dynamics and tradeoffs that emerge from the different sectors driven by the different representations of population and GDP uncertainties and feedback.

2.2. Methods—GCAM Overview and Different Regimes of Model Behavior

This study focuses on the impact of population and economic growth uncertainty on consumption and production. To capture these dynamics, we use GCAM version 6.0 (version-specific documentation at: <http://jgcri.github.io/gcam-doc/v6.0/toc.html> and model version at: <https://github.com/JGCRI/gcam-core/releases/tag/gcam-v6.0>), which takes GDP and population as exogenous drivers. GCAM is a global multisector model that decomposes the world into 32 geopolitical regions, 384 land-use regions, and 235 water basins (Calvin et al., 2019). GCAM consists of coupled representations of the Earth's climate, economic, hydrologic, land-use, and energy systems, as well as a detailed representation of the energy sector, water, and land-use change that uses a logit model to adjust market prices until supply and demand are in equilibrium for all markets.

The core energy module consists of representations of depletable primary resources and renewable sources, as well as processes that transform these resources into final energy carriers, which are ultimately used to deliver goods and services to end-use sectors. The agriculture and land-use components represent the competition for land between alternative uses in each of 384 land-use regions (the intersection of GCAM's 32 geopolitical regions and the 235 hydrological basins). Traditional biomass is represented by exogenous supply curves that account for the opportunity cost of time to capture the declining preference for traditional biomass (the collection of traditional biomass requires labor that becomes more expensive as incomes increase). GCAM models food demand (Edmonds et al., 2017) in a way that is responsive to both consumer income and food prices (Narayan et al., 2021). Demand for staple and non-staple food commodities are modeled separately, with demand for staples being relatively less elastic than for non-staples. Water supply in GCAM is modeled using three different sources: surface water and renewable groundwater, nonrenewable groundwater, and desalinated seawater (Hejazi et al., 2014). Similar to the energy sector in GCAM, these water sources compete using a logit structure based

on price, balancing supply and demand by determining an equilibrium regional shadow price for water. Surface water is typically used first and in greater quantities than other water sources because it is the least expensive. GCAM estimates 24 GHGs and air pollutants endogenously based on the energy, agricultural, and land-use systems. Energy inputs and outputs drive emissions in the energy system. In the agriculture and land use system, emissions are driven by output. Emissions in GCAM are calculated depending on the outcomes of different drivers (such as energy consumption, land use, and population). Emissions are modeled at the regional level, water basin, technology mix, and abatement measure. GCAM is described in more detail by Calvin et al. (2019).

The multisectoral implications of uncertainties in population and GDP depend critically on future economy-wide technological transitions. From a GCAM modeling perspective, the same driving GDP and population trajectories can produce fundamentally different GCAM outputs based on other model settings and assumptions. Therefore, to test the robustness of insights derived from driving GCAM with these large ensembles, all of the GDP and population scenarios described in the previous section are simulated with GCAM in two different configurations that have resulted in qualitatively different regimes of behavior in past experiments: The first, labeled “Reference” in this paper, assumes that the future energy system largely follows historical trends. The second case, an alternative “low carbon” scenario, assumes an economy-wide global transition toward technologies such as renewables, carbon capture and storage, biomass, and direct air capture based on the work of Iyer et al. (2022) and Ou et al. (2021). This scenario is also characterized by transitions in the land-use system to satisfy the increased demand for bioenergy in the energy system and afforestation. The endogenous transitions in the land-use system are a key feature of this scenario. The transitions can place pressure on land use, particularly because there exists a hard limit to land available globally.

2.3. Methods—Metrics

To investigate the impact of compounding population and GDP uncertainty across the distribution of outcomes, we adapt the quantile magnification concept from flood frequency analysis (Vogel et al., 2011). This measures the change in magnitude of each quantile of a metric, Q , due to some factor, A :

$$M_p(A) = 100 \times \frac{Q_p(A) - Q_p}{Q_p}$$

where Q_p is the p th quantile of metric Q and $Q_p(A)$ is the p th quantile of metric Q with factor A applied. Note that p is the non-exceedance probability of Q_p , or the probability that a randomly selected observed Q will be less than or equal to Q_p . The metric $M_p(A)$ is adapted from non-stationary flood frequency analysis where the focus is on the disparate impact of climate change on different design floods (Vogel et al., 2011). For instance, changes to the average or median flood are likely of much less concern to planners and engineers than changes to extreme floods (e.g., 100-year flood). By evaluating $M_p(A)$ across the scenario ensemble we can assess how factor A impacts each part of the distribution of outcomes. Whereas statistics like the mean, coefficient of variation, coefficient of skewness, and coefficient of kurtosis provide summary information about changes to the distribution shape, quantile magnification reports changes to each outcome quantile directly. In this analysis, magnification is used to assess the impacts of adding additional sources of uncertainty, so factor A is the addition of GDP uncertainty on top of population uncertainty, for example. Thus, $M_{0.99}$ would report the change in the 99th percentile (upper tail) due to the addition of GDP uncertainty.

$M_p(A)$ can be computed directly from the Monte Carlo replicates, but sampling error in the quantiles introduces noise that can obscure magnification trends across quantiles. Alternatively, one can estimate $M_p(A)$ by first fitting a distribution to the metric Q and computing $M_p(A)$ on the quantiles of the fitted distribution. The resulting smooth magnification factors retain the trends observed in the raw $M_p(A)$, but with sampling error noise removed. The smooth magnification factors plotted in Figures 3, 6, and 9 are generated by first approximating the probability density functions of Q with and without factor A using kernel density estimation, then computing $M_p(A)$ from the quantiles of the fitted distributions.

3. Results

3.1. Implications of the Representation of Population and GDP Uncertainty

How population and GDP uncertainty and feedback is represented in the model has important implications for multisectoral metrics. The global distributions for staple food prices, water withdrawal, final energy, and CO₂ emissions in 2100 are shown by the probability density function (PDF) in Figure 2 for each of the four scenarios

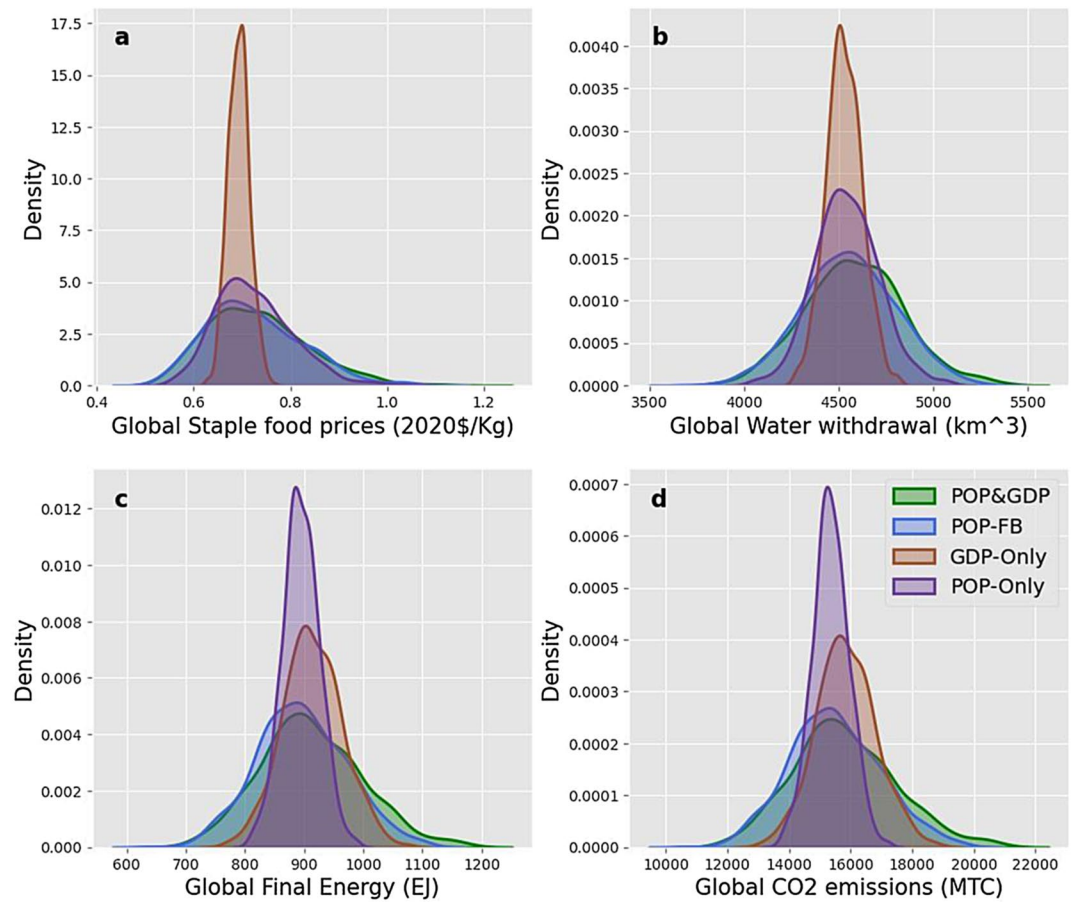


Figure 2. Probability density function (PDF) of the distribution of global staple food prices, global water withdrawal, global final energy demand and global CO₂ emissions across all scenarios in 2100 under the reference case.

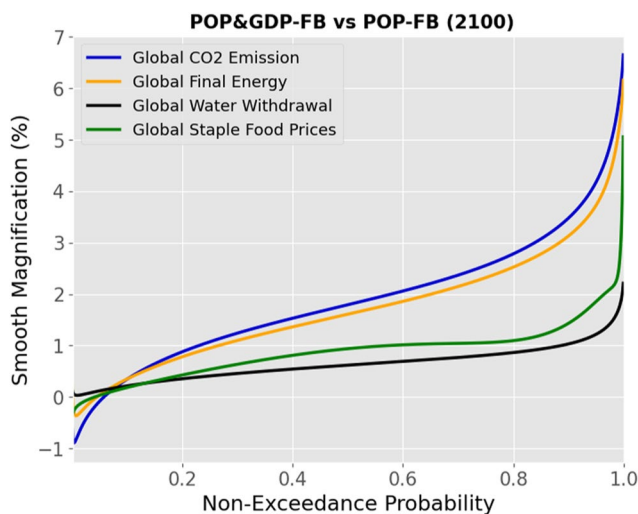


Figure 3. Magnification versus non-exceedance probability for global staple food prices, water withdrawals, final energy consumption, and CO₂ emissions due to GDP uncertainty under the reference case in 2100. The p th quantile of metric Q , Q_p , is the value of Q with non-exceedance probability p .

representing different methods of incorporating these uncertainties and their interactions. Comparing the GDP-Only and POP-Only PDFs for each metric, we can see whether GDP or population growth is a stronger driver of uncertainty in a given metric. We find that population growth uncertainty is a stronger driver of staple food prices (Figure 2a) and water withdrawal (Figure 2b) while GDP growth uncertainty is a stronger driver of final energy (Figure 2c) and CO₂ emissions (Figure 2d). Other studies have similarly found the population to be a main driver of food and water outcomes (Wiltshire et al., 2013). In general, population directly affects the overall demand for food (as calories consumed). For example, increases in population increase consumption while income (GDP) mainly affects consumption through preferences for the types of foods consumed due to income elasticity. For staple foods in particular there is a lower elasticity of demand, so more people translate rather directly to higher demand, which in turn affects prices. For prices of some other foods, such as meats, GDP uncertainty would be expected to play a more important role. We also see that the distribution of staple prices under POP-Only has a heavy upper tail, suggesting that food prices can start to spike as the population rises and constraints on land and water limit the ability to meet the growing demand efficiently.

Water withdrawal is also more strongly affected by population than GDP. As the population increases, there is a greater demand for water for drinking, sanitation, irrigation, and industrial purposes. This direct relationship between water use

and population size can lead to a strong correlation. Therefore, a shift in any direction of population growth propagates that uncertainty in water withdrawal and use. In contrast, while economic development can lead to increased water use in certain sectors (e.g., industrial processes), the relationship between GDP and water use is often more complex. For example, as countries develop economically, the changes in consumption patterns, including dietary and lifestyle changes and efficient water use technologies, can offset the increase in water demand. On the other hand, GDP is a stronger driver of final energy demand, reflecting sizable increases in energy consumption with higher income levels. Higher energy use with higher GDP also translates to higher CO₂ emissions in the reference scenario.

Our results also show that representing feedback between population and GDP changes the distributions in important ways. With feedback between population and GDP (POP-FB and POP&GDP-FB), all metrics demonstrate increased variability and heavier upper tails. This effect is more pronounced for water withdrawal, final energy, and CO₂ emissions, but is also present for staple food prices. Importantly, these growing upper tails represent the most undesirable realizations of the outcomes—those that present the greatest challenges to sustainable development. High staple food prices threaten the affordability of food for vulnerable populations. High water withdrawal presents risks for water scarcity and water stress. While higher outcomes of final energy could reflect increased energy access, such high energy use is largely fossil based in the reference scenario. Without representing feedback between population and GDP uncertainties, the increased risk of unfavorable high-tail outcomes would be underestimated.

In addition, results show that the distributions change when both population and GDP growth are represented (POP&GDP-FB). In particular, there is a differential response in the upper tails with both uncertainties, which is more pronounced for final energy and CO₂ emissions. When accounting for both uncertainties together, the likelihood of unfavorable (high) outcomes increases. In other words, compounding economic and population growth uncertainties increases tail risks for these multisector outcomes of interest. We examine this compounding impact in the next section.

3.2. Impact of Compounding

To investigate the issue of compounding uncertainties, we next focus on how the multisector metrics highlighted in Figure 1 are magnified under population uncertainty with feedback to GDP (POP-FB) correlated at 78% and the combined population and GDP uncertainty (POP&GDP-FB) correlated at 38%. Figure 3 shows the magnification of each metric when GDP uncertainty is also included (comparing the POP-FB and POP&GDP-FB scenarios). We see that the addition of GDP uncertainty increases each outcome (magnification is positive) across most of its distribution. This is most pronounced in the upper tail of the distribution, but this does not impact all sectors equally.

For global final energy consumption and CO₂ emissions, adding GDP uncertainty magnifies the median of their distribution by approximately 1.6%–1.8%. However, the addition of GDP uncertainties increases each metric by 6%–6.5% at the upper tail. The upper tails for these metrics reflect possible futures with both high population growth and high GDP growth, with both forces driving higher energy use and subsequently higher emissions, in a manner that results in higher tail outcomes. Although the median estimate remains largely unaffected by the addition of GDP uncertainty, the addition has a disproportionate change on the 1:100 outcome. Thus, correctly accounting for uncertainty in multiple key drivers is critical to understanding severe outcomes, even though mean behavior may not differ significantly.

For global staple food prices and water withdrawal, adding GDP uncertainty has an even smaller impact at the median (approximately 1% and 0.6%, respectively). However, there is a sharp increase in magnification at the extreme upper tail for staple food prices, reaching about 5%. The GCAM realizations that correspond to the upper tail are driven primarily by realizations with high populations and GDP per capita values spanning a range similar to the entire ensemble. The high demand, combined with limits to the availability of the land and water needed to meet that demand, results in very high prices at the tail of the distribution—a magnification that is only seen when population and GDP uncertainties compound.

The addition of GDP uncertainty does not increase the magnification at the extreme upper tail in global water withdrawal to the same extent as other metrics (magnification reaches approximately 2.2% at the extreme tail). Water availability, demand, and withdrawal vary significantly across regions. Local factors such as climate and geography play a crucial role in determining water supply and, consequently, the water price and water withdrawal

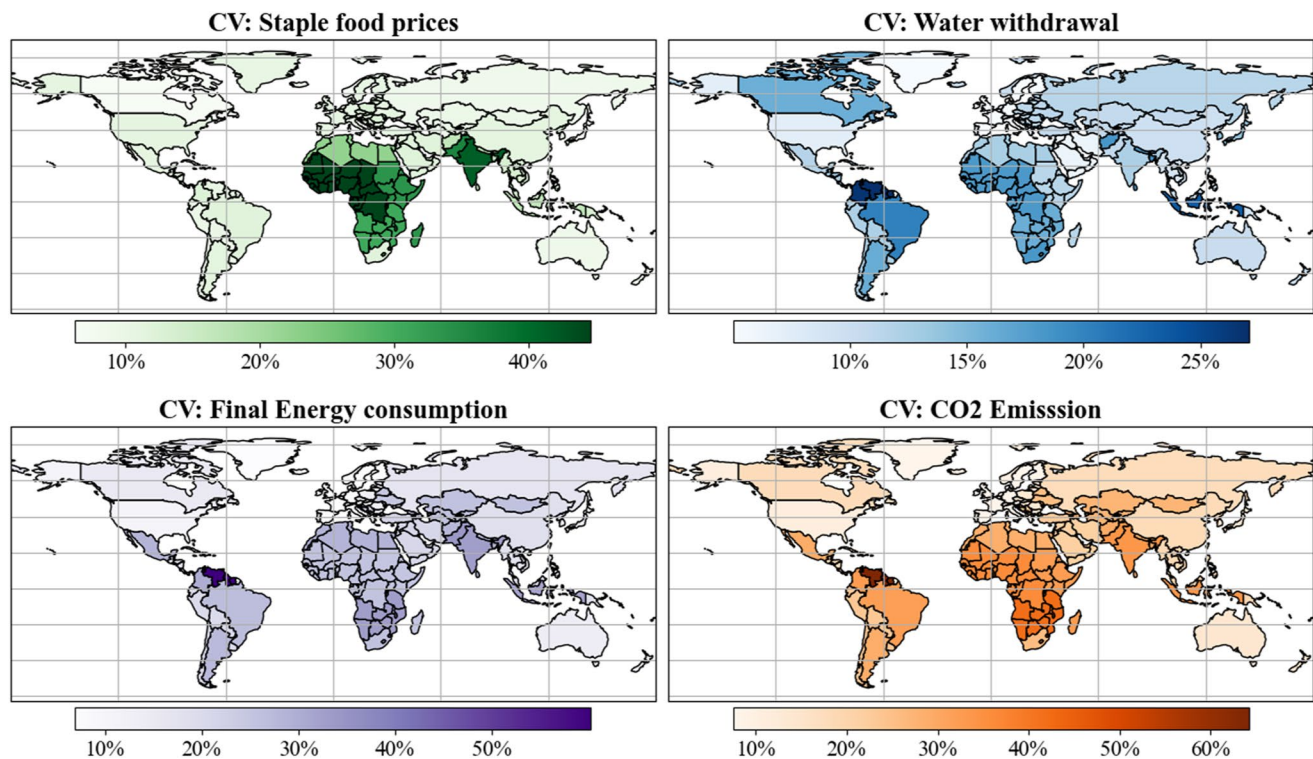


Figure 4. Regional uncertainty in the reference case for combined population and GDP uncertainty (POP&GDP-FB), represented by the coefficient of variation (CV) in 2100.

in each region, in addition to broader economic interactions across sectors and regions. Therefore, the impact of adding GDP uncertainty on water withdrawal will depend on the specific regional context and the relative importance of economic factors in driving water use, which may explain the lower magnification that the addition of GDP uncertainty causes at the global level compared to other metrics.

3.3. Regional Impact of Combined Population and GDP Uncertainty in the Reference Scenario

Uncertainty in economic and population growth varies across regions due to different levels of development, cultural and societal preferences, and can differ dramatically from global behavior. Multisector system representations enable us to examine the impact of population and GDP growth uncertainty on complex dynamics between multisectoral outcomes and regions. Figure 4 presents the coefficient of variation (CV) for staple food prices, water withdrawal, final energy consumption, and CO₂ emissions across different regions, as influenced by the combined population and GDP uncertainty (POP&GDP-FB).

As an example, Western Africa and India see greater uncertainty relative to other regions in staple food prices due to higher population and GDP growth uncertainty than other regions. Agriculture is a significant source of employment and income in these regions and many people rely on staple foods for daily sustenance (Abbas, 2022; Guntukula, 2020; Olanipekun et al., 2019). In both West Africa and India, the coefficient of variation for staple food prices in 2100 is higher than GDP, indicating a greater degree of variability in food prices relative to GDP growth. For both regions, the values are similar: in West Africa, the CV for staple food prices is 45% and 27% for GDP growth, while in India, the coefficient of variation stands at 42% for staple food prices and 26% for GDP. In contrast, there is a significant difference in population growth uncertainty between India and Western Africa. Figure 5 displays distributions of population for each region at different time slices. While uncertainty increases over time for both regions, notably the movement right of the probability density of Western Africa indicates substantially more population growth than in India is likely, even accounting for uncertainty. These regional differences in population appear to primarily drive different ranges in staple food price changes for each

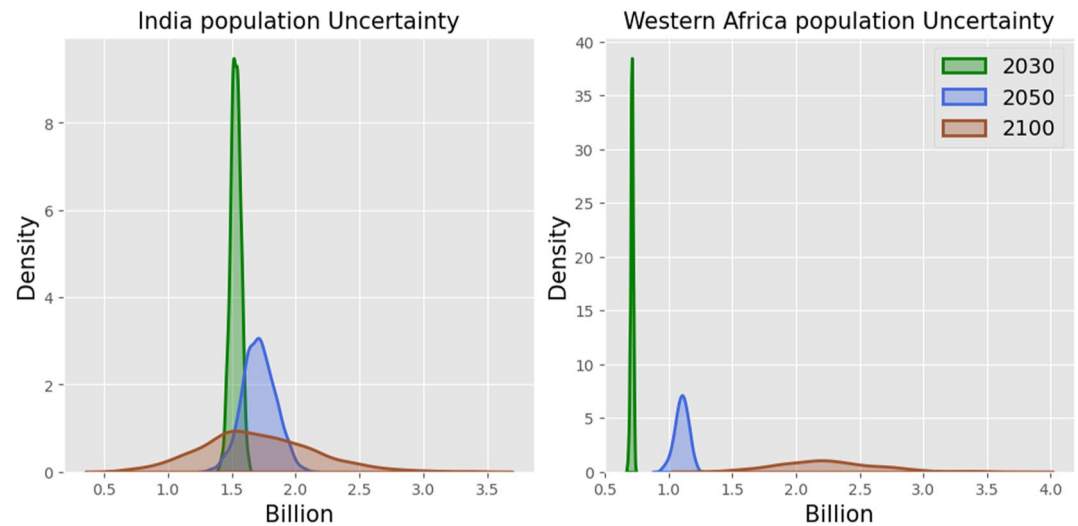


Figure 5. India and Western African population distributions.

region, despite the CV-measured uncertainty in each region's staple food prices being comparable. Across our ensemble, staple food prices in Western Africa rise between 136% and 999% over 2020 levels by 2100 (5th and 95th percentiles). In India, staple food prices could increase between -6% and 179% , significantly contrasting the range in West Africa.

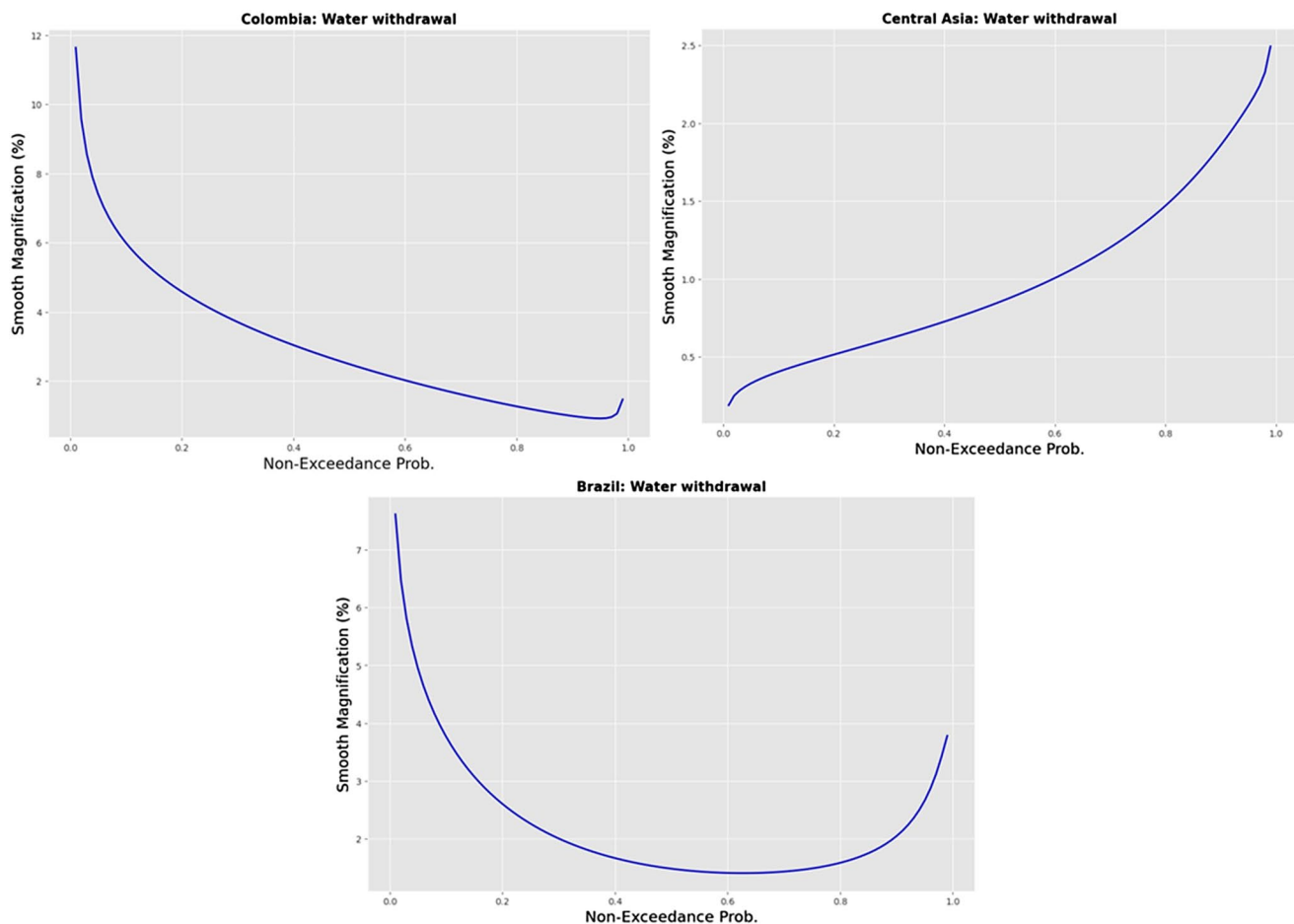


Figure 6. Water withdrawal magnification versus non exceedance probability for Colombia, Western Africa and Brazil under the reference scenario in 2100.

Water withdrawal is most uncertain in South America, Western Africa, Southern Africa, Canada, and Southeast Asia. However, the degree to which water withdrawal relates to the risk of water scarcity is heavily dependent on the region, (e.g., the region's water supply, current levels of withdrawal, potential population, and economic growth, etc.). Focusing on Western Africa, it is likely that the uncertainty in water withdrawal is strongly related to the uncertainty in agricultural demand arising from population uncertainty.

While there are likely interesting patterns to uncover in the dynamics of variance and central tendency across regions and sectors, our global results motivate us to focus on understanding patterns of quantile magnification. Examination of magnification curves across regions and sectors highlighted consistent shapes of magnification curves emerging. Figure 8 provides some examples of the kinds of shapes that occur.

We characterize these shapes by performing principal component analysis (PCA) for each metric. Each GCAM region's magnification curve for that metric is represented by 100 quantile values, and these are used as the observations for the PCA. By projecting into the space defined by the first two principal components, we can characterize a magnification curve (like Figure 6) by its location in this space. Figure 7 contains plots for each metric and region in the metric-specific two-dimensional PC space. Three distinct types of magnification emerge across regions and metrics, indicated by their own regions of the PC-space that we have annotated. We have also annotated which of these PC-regions the global magnification curves (Figure 3) correspond to. High extreme magnification (see Figure 7, Central Asia) means that the upper tail of outcomes, which in this study present challenges, are becoming disproportionately more extreme (worse), compared to the mean. The low extreme magnification (see Figure 6, Colombia) means that the lower tail of outcomes, which in this study are generally lower outcomes for the metric (lower food prices, water withdrawal, final energy consumption, or CO₂ emissions) are becoming disproportionately larger (worse) relative to the median due to compounding. The U-shaped magnification (see Figure 6, Brazil) indicates that both the lower tail and the upper tail are magnified relative to the median due to compounding. In the case of water withdrawals, this means that both high end (e.g., worst case) and low end (e.g., best case) withdrawals are becoming disproportionately larger, potentially presenting significant challenges in future planning. Indeed, each type of compounding presents unique challenges and opportunities for future planning which would be missed by focusing on summary statistics (like the mean or variance) alone.

Most regions show high extreme magnification of uncertainty for staple food prices, except for Brazil, Pakistan, and South America-Northern, which have both low and high extreme magnification, and Colombia, with a lower tail magnification. It is worth noting that in Brazil and Southern America as a whole, staple food prices are generally less uncertain than in Pakistan. However, compounding GDP uncertainty with population magnifies uncertainty in food prices similarly in both regions, creating risk at both the lower and upper tail. By 2050, both in Brazil and Pakistan, non-staple food consumption will overtake staple food consumption. The majority of regions also show high extreme magnification of uncertainty for water withdrawals. There is more regional variation in the magnification pattern for final energy and CO₂ emissions, but the plurality of regions still maps to high extreme magnification.

Overall, the compounded impact of population and GDP uncertainty differs by sector and region. It is critical to model these impacts in an integrated, multisector multi-region framework that attempts to account for uncertainties. Although population and GDP are two of the most critical drivers of the GCAM, other factors, such as prices and resource availability, are also significant drivers. The level of compounding observed across regions and sectors under population and GDP uncertainty highlights the importance of considering compounding uncertainty and its impact on other drivers.

3.4. Compounding Impact in a Low Carbon Transition Scenario

GCAM can produce multiple regimes of behavior even for fixed socio-economic drivers. For example, the same population and GDP trajectories can produce fundamentally and qualitatively different outcomes based on other model settings and assumptions, such as resource availability, technology, policies, and consumers and producers' preferences. Here we investigate our metrics of interest under a low carbon transition scenario by changing the settings in the model to include spatially heterogeneous constraints on land availability and CO₂ emissions from the fossil fuel and industrial sector. Figure 8 compares the evolution of uncertainty over time for each metric for the reference and low-carbon transition scenarios under the combined population and GDP uncertainties.

The dynamics in this alternate case in response to the same distributions of GDP and population as were used with GCAM's reference settings are quite different across sectors. The energy sector leads towards increased

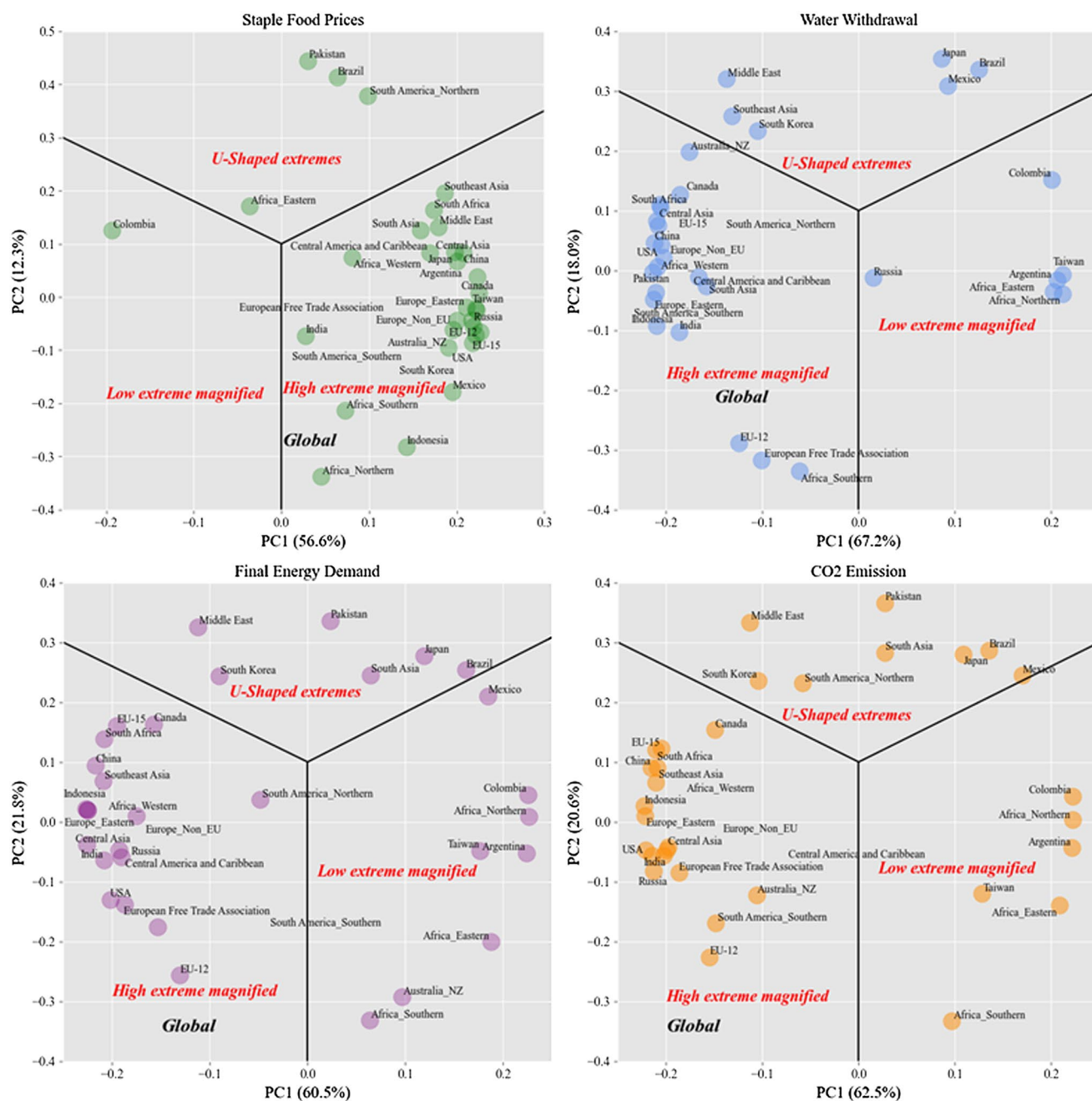


Figure 7. Clustering of regional magnification (compounding) for staple food price, water withdrawal, final energy demand and CO₂ emissions for the reference scenario.

biofuel production, energy efficiency improvements, and electrification from renewable sources. These dynamics contribute to a decline in final energy consumption, as shown in Figure 8. The expansion of low-to zero-carbon energy sources also leads to a decoupling of energy and emissions. By imposing a limit on emissions, the low carbon scenario also decouples population and GDP growth uncertainty from emissions. In the land use and water sectors, the constraints from this alternative future scenario drive three main dynamics. First, with a price on emissions from land use change, the system responds by protecting and expanding natural land (i.e., afforestation), which limits land availability for agricultural expansion. Second, with an emissions limit, the energy system turns increasingly to bioenergy, expanding agricultural land use for bioenergy production and reducing the portion of available cropland for food production. Both dynamics lead to agricultural intensification to meet

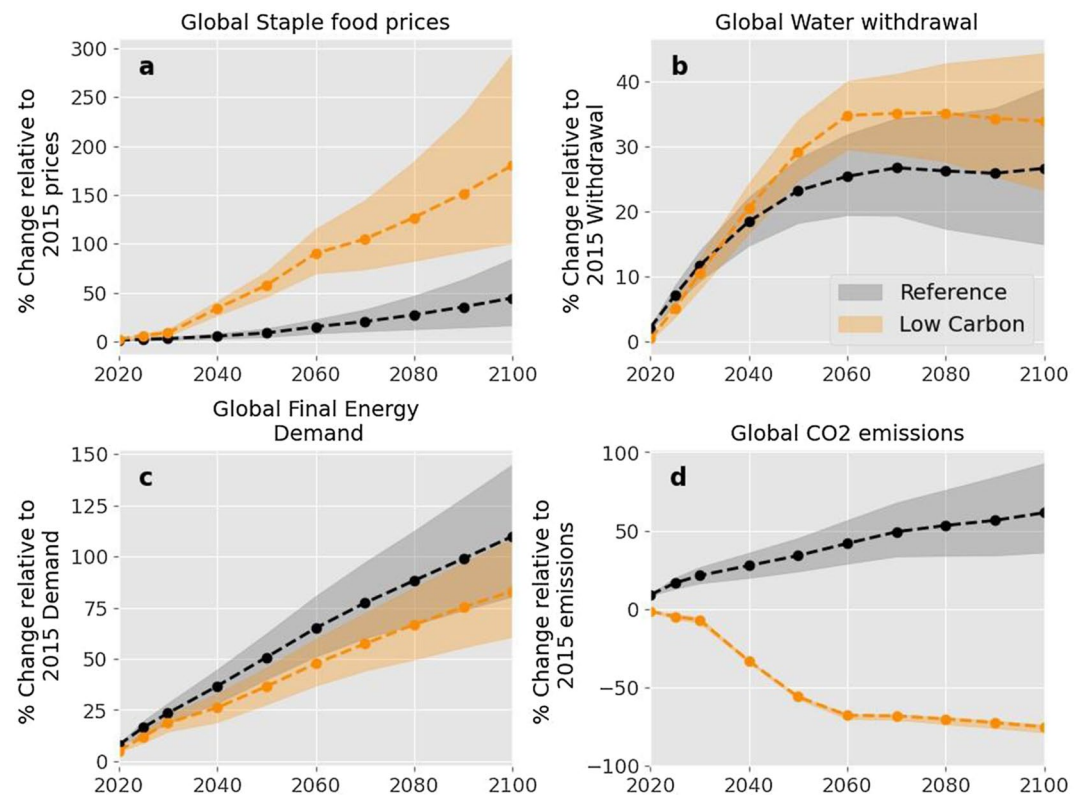


Figure 8. Change in global CO₂ emissions, final energy consumption, global water withdrawal, and staple food prices, relative to 2015 under reference and low carbon transition scenarios.

food demand. Third, agricultural intensification contributes to increased water withdrawal (i.e., increased irrigation to increase crop yields). As a result, global staple food prices are significantly higher under the low carbon scenario than the reference case, and global water withdrawal is higher as well. While the uncertainty in final energy and emissions is narrowed by the low carbon transition, it is widened quite substantially for staple food prices. Increased competition for land, agricultural intensification, increased water withdrawal, and increased food demand all contribute to increasing global food prices. As such, uncertainties in land, energy and water outcomes all propagate to increase food price uncertainty, particularly at the upper tail (see Figure 9), and the burden of uncertainty has shifted to different sectors than was seen in the reference case.

The alternative future with an emission constraint decouples the compounded effect of population and GDP uncertainty on global CO₂ emissions, as shown via magnification curves in Figure 9d. However, the uncertainty effect of this constraint can be analyzed through other sectors. The uncertainty compounded in final energy consumption is not substantially different from the reference case. However, we observe a slight decrease in the upper tail. This is due to energy efficiency improvements, and increased electrification from renewable energy sources which slightly reduce the impact of compounded population and GDP uncertainty on final energy consumption. It is also important to note that in this case much of the concern about upper tail energy use outcomes is alleviated since energy use is decoupled from emissions. However, some concerns about high energy use remain, such as the implications of large amounts of bioenergy. The magnification of global water withdrawal in this case follows a similar trend as final energy consumption. Despite increased water withdrawal under the low carbon case, the magnification due to the addition of GDP uncertainty is only slightly less than in the reference case.

For global staple food prices, we see that combined GDP and population growth uncertainty compounds more in the low carbon scenario than the reference scenario along the whole distribution and especially at the upper tail. For example, combining GDP uncertainty with population uncertainty (i.e., moving from a POP-FB to POP&GDP-FB) magnifies the median global staple food prices by approximately 2.5% in the low carbon scenario (compared to about 1% in the reference scenario). However, the effect of compounding uncertainty is particularly pronounced at the upper tail where we observe a magnification of about 15%, compared to a 5% increase in the

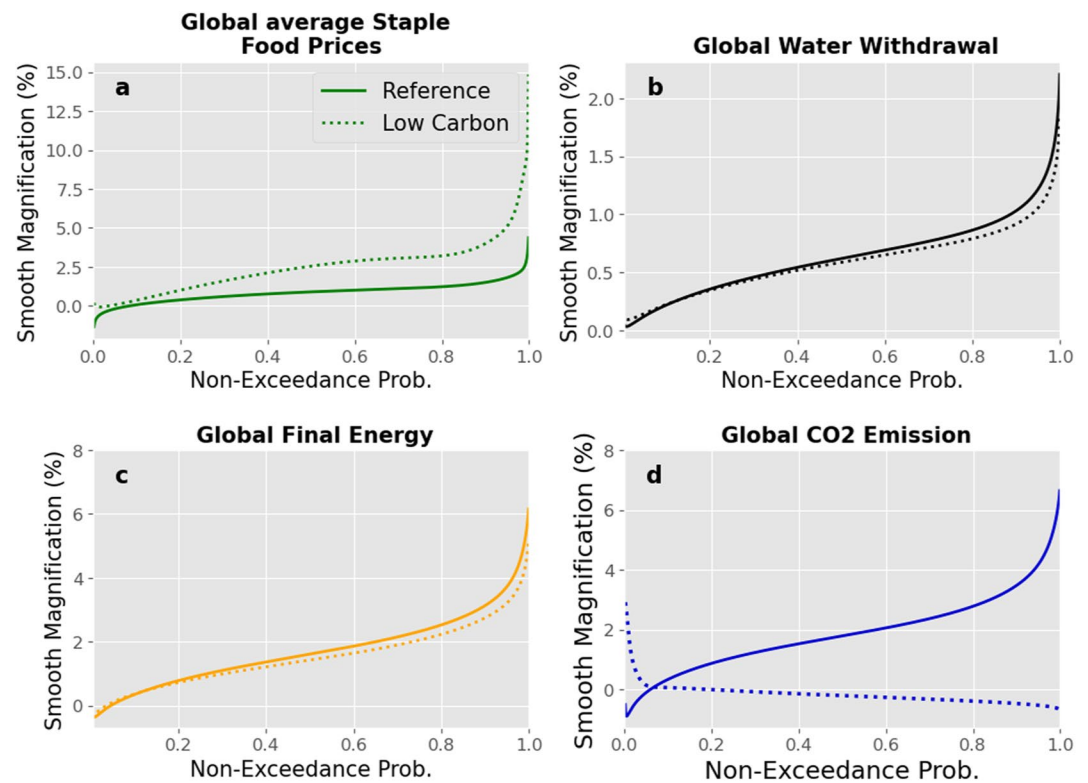


Figure 9. Magnification versus non-exceedance probability of global CO₂ emissions, final energy consumption, water withdrawals, and food prices under the reference scenario (solid line) and an alternative low carbon transition scenario (dashed line) in 2100.

reference scenario. This implies a greater chance of food prices experiencing a sharp increase. The compounding effect of GDP and population uncertainty on staple food prices is stronger in the low carbon case because the emergent dynamics driven by the emissions constraint (i.e., afforestation, shift toward bioenergy, competition for land, increased need for agricultural intensification and water) all lead to higher staple food prices. The addition of population and GDP uncertainty, and in particular realizations of high population growth and low GDP growth (which results in larger increases in demand for staple foods), further stresses land availability, amplifying the compounding effect. This suggests the need to investigate additional high population growth, and low GDP growth scenarios that are likely to lead to tipping points or particularly vulnerable futures (O'Neill et al., 2020). Failing to account for compounding uncertainties could lead to underestimating the true impact on food prices under an energy transition scenario.

4. Discussion and Conclusions

This study explores the impact of economic and population growth uncertainty on long-term multisectoral outcomes using the global, integrated multisector model GCAM. The integrated nature of GCAM allows the evaluation of how uncertainty propagates between sectors and across regions through trade, as well as how alternative GCAM scenarios might impact these dynamics. Following the approach of Morris et al. (2022), we develop four large ensembles of scenarios that represent alternative approaches to capture uncertainty in population and GDP growth, and their feedback. Our analysis focuses on how these interacting uncertainties affect staple food prices, water withdrawals, CO₂ emissions, and final energy consumption. We find that considering population and GDP uncertainty together (compounding) results in more extreme outcomes than when considering those uncertainties in isolation (Figure 2). We also find that the strategy for joint sampling (i.e., the nature of the feedback between population and GDP), can have differential impacts across the outcome distribution, often magnifying tail risks (Figure 3). This concentrated shift in the extremes can have a significant impact on risk analyses, while not significantly changing the mean or variance. Thus, scientists must carefully weigh the impact of their modeling

choices, especially the way they model correlated uncertainties, by scrutinizing their impact on analysis-relevant outcomes. Put another way, large ensembles of scenarios deployed in a multisectoral model, accounting for the potential for uncertainties to compound, reveal key risks that may be missed in sensitivity analysis.

The multi-sector response to compounding population and GDP uncertainties also varies significantly across regions and metrics (Figure 4). For example, staple food prices in western Africa and India exhibit much more variability than the rest of the world, while final energy consumption and CO₂ emissions are most uncertain in northern South America. Uncertainty in food prices in western Africa and India is largely driven by population uncertainty relative to GDP uncertainty, which is substantial in both of those regions (Figure 5). The compounding influence of GDP uncertainty on top of population uncertainty magnifies the extreme high food prices in our ensemble in most regions (Figure 7). That is, the addition of GDP uncertainty makes the highest food price scenarios disproportionately more extreme. Looking across other metrics, we observe a greater diversity of magnification patterns. For instance, for water withdrawals, most regions still exhibit upper tail magnification, but some regions exhibit U-shaped magnification. For those regions, the imposition of GDP uncertainty simultaneously makes the highest withdrawal scenarios disproportionately higher and the lowest withdrawal scenarios disproportionately higher. These regionally differentiated regimes of behavior represent unique challenges and opportunities for scientists when evaluating uncertainty in multisector projections. Failing to account for the impact of compounding uncertainties can misrepresent tail risks, particularly in regional analyses.

Our analysis highlights that uncertainty propagation and compounding are affected by assumptions about broader future trends by evaluating a low-carbon transition scenario. This scenario is characterized by increased energy efficiency, adoption of renewable energy, and greater use of biofuels. This alternative scenario resulted in an overall reduction in final energy consumption and CO₂ emissions but increases in food prices and water withdrawals due to greater competition for land and water resources (Figure 8). Both the mean and the variability of food prices increase under the low-carbon transition scenario, which is consistent with prior research that showed a significant link between economy-wide emissions reduction and the prices of key agricultural commodities (Dolan et al., 2022; Hasegawa et al., 2018). Our analysis also shows that magnification patterns vary substantially between the reference and low-carbon scenario for food prices, but not for water withdrawal and energy consumption. While our analysis showed an increase in the mean and variance of final energy between the low carbon and reference scenarios (Figure 8), the magnification dynamics quantifying the effects of compounding GDP and population uncertainty remain virtually unchanged (Figure 9). In contrast, the magnification of food prices due to compounding GDP and population uncertainty was much higher in the low-carbon scenario. This highlights the difficulty of uncertainty quantification for multisector systems, where input uncertainties can interact and transmit nonlinearly to uncertainties in outcomes across regions, sectors, and broader behavioral regimes.

Our study illustrates the need for a multisectoral and multi-regional understanding of the coupled human-Earth system, as the interactions between different sectors and the propagation of uncertainties can have significant implications for long-term development. As such, the representation of feedback and correlations in models need to be carefully considered. In addition, sensitivity analysis may miss human-relevant outcomes that are only revealed through large ensembles of multisectoral models with careful representation of correlated uncertainties. This study has focused on compounding population and GDP uncertainty. Future research could further explore compounding uncertainties and their cascading effects on different drivers of uncertainty to enhance our comprehensive understanding of the complex nature of multisectoral systems.

4.1. Limitations

While our approach provides valuable insights into the impact of compounding uncertainties in population and GDP growth on multisectoral outcomes, it is important to note that this approach is designed to answer “what-if” questions about the impact of compounding uncertainties in population and economic growth, rather than to provide future range or tail risk of uncertainties in food, energy, and water consumption and prices. Any such analysis would require information on the complete set of influences on future energy, land use, and water supply and demand, including changes in rates of technological change, climate change impacts, and policies on production and consumption. Nonetheless, this analysis highlights the potentially significant implications of compounding population and income growth uncertainties on the long-term outcomes of the energy, water, and land use systems to deliver the food, energy, and water required by future populations. Future work can explore uncertainties in other drivers and their multisectoral implications in detail.

Data Availability Statement

The model used for this analysis is publicly available (Bond-Lamberty et al., 2021). The model output data on which this article is based are available in Kanyako (2023), which contains the population and GDP samples, key model outputs, and the Python Jupyter notebook employed to generate the figures. The process for generating the population and GDP samples is described in Morris et al. (2022).

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