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Sensitivity of projected long-term CO_2 emissions across the Shared Socioeconomic Pathways

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Scenarios showing future greenhouse gas emissions are needed to estimate climate impacts and the mitigation efforts required for climate stabilization. Recently, the Shared Socioeconomic Pathways (SSPs) have been introduced to describe alternative social, economic and technical narratives, spanning a wide range of plausible futures in terms of challenges to mitigation and adaptation[1]. Thus far the key drivers of the uncertainty in emissions projections have not been robustly disentangled. Here we assess the sensitivities of future CO_2 emissions to key drivers characterizing the SSPs. We use six state-of-the-art integrated assessment models with different structural characteristics, and study the impact of five families of parameters, related to population, income, energy efficiency, fossil fuel availability, and low-carbon energy technology development. A recently developed sensitivity analysis algorithm[2] allows us to parsimoniously compute both the direct and interaction effects of each of these drivers on cumulative emissions. The study reveals that the SSP assumptions about energy intensity and economic growth are the most important determinants of future CO_2 emissions from energy combustion, both with and without a climate policy. Interaction terms between parameters are shown to be important determinants of the total sensitivities.

Counterfactual or baseline scenarios of future greenhouse gas emissions play a crucial role in the scientific analysis of climate change, but they also increasingly matter in the political debate. Long-term projections of socioeconomic and emission scenarios are needed to be able to assess future climate change, and its physical and economic impacts. Emission reduction policies, including several of the Nationally Determined Contributions (NDCs), are expressed as reductions relative to emissions projections. Moreover, baseline emissions are one of the most important drivers of mitigation costs[3–5]: the higher the expectations of future emissions in the absence of climate policy, the greater the mitigation effort for a given climate target, which translates into higher policy costs and technological transformation requirements.

Although long-term emissions projections are needed for decision-making, there is large uncertainty in their estimates. Several emission scenarios have been generated by the integrated assessment model (IAM) research community over the years. These include the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios[6] and the new Shared Socioeconomic development Pathways (SSPs)[7–11].

Scenarios generated by several models allow one to quantify both parametric and model uncertainty, which have been identified as a major source of uncertainty. Moreover, diagnostics of IAM is a relatively nascent field that is growing in importance to help validate models. Hence, it is useful to disentangle the key drivers of the uncertainty in emissions projections because that understanding can help design hedging strategies.

Building baseline scenarios is a daunting task that requires projecting forward multiple factors driving emissions and accounting for the large uncertainties characterizing them. To date the research community has relied on multi-scenario and multi-model comparisons to help quantifying the uncertainties surrounding future emissions. As no single model projection nor individual scenario will probably be exactly true, it is extremely useful to gauge the relative importance of drivers of these scenarios and allocate research efforts to strategically minimize uncertainties. In such an exercise, it is worth also to design additional scenarios that are not necessarily self-consistent with the original narratives, but still may bring important insights into surprises and risks we might want to hedge against. However, so far limited attention has been given to the understanding of the sensitivity of projected emissions to the underlying drivers that together define a specific narrative. The aim of this paper is to fill this gap by systematically decomposing the individual and combined influence of each driver on greenhouse gas emissions in a multi-model perspective.

IAMs have been subjected to sensitivity analyses in the past. However, most of these analyses have focused on either a small set of models, or on individual sensitivities[12–18] (see Supplementary Information for a literature review). Individual sensitivities are computed by varying just one factor at a time. However, this allows for the computation of only the individual effects of a particular factor change, disregarding interactions among factors. A more refined methodology is employed here to also capture nonlinearities and interactions across factors at limited computational cost. Thus, this paper goes beyond the existing literature on three main issues:

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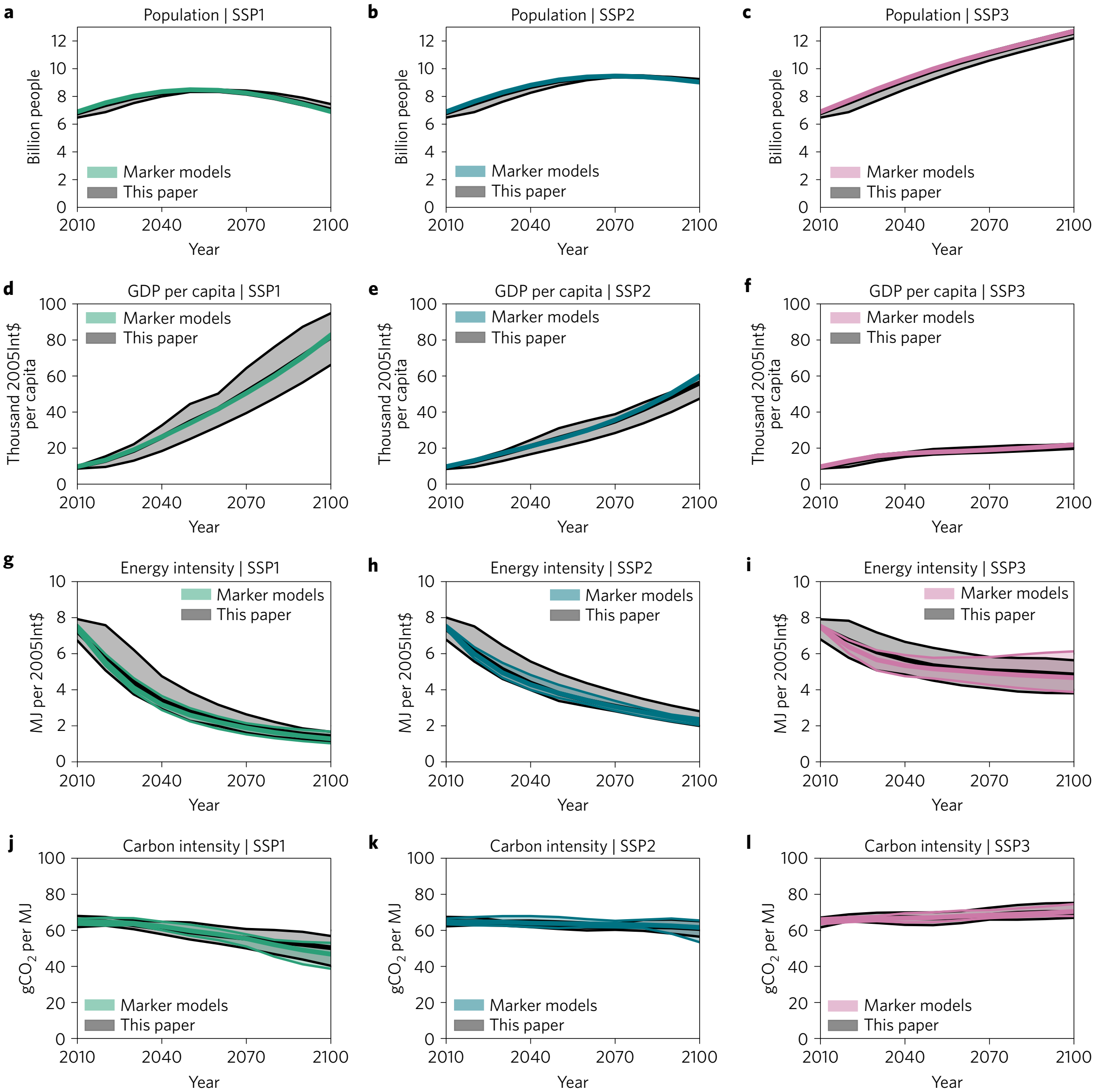

Figure 1 | Main CO_2 emission drivers for the first three SSP scenarios. In colour, the range spanned by SSP marker models; in grey (and delimited by black lines), the range of the models participating to this study. **a–c**, Yearly world population. **d–f**, Yearly world GDP (PPP) per capita. **g–i**, Yearly world primary energy supply per unit of GDP (PPP). **j–l**, Yearly world CO_2 FFI emissions per unit of primary energy supplied. Central black lines are means across models.

we use the SSPs, we carry out a multi-model comparison, and we evaluate both individual and total sensitivities.

The SSP framework has identified five main narratives, which span the mitigation and adaptation challenges space. In this paper we focus on the first three scenarios, namely SSP1 (ref. 19), SSP2 (ref. 20) and SSP3 (ref. 21). These scenarios represent low, intermediate and high challenges to both mitigation and adaptation. Our variable of interest is the global cumulative CO_2 emissions from fossil fuels and industry over the next decades, a good proxy for changes in relevant climate variables, such as average surface temperature of the Earth[22,23]. We focus on energy-related emissions given their predominant role in future greenhouse gas atmospheric concentrations, and their ease of comparability across the differently structured models. Six IAMs have participated in the study: GEM-E3-ICCS[24], IMAGE[25], IMACLIM[26], MESSAGE-GLOBIOM[20], TIAM-UCL[27] and WITCH-GLOBIOM[28].

These models have previously contributed to major scientific and policy-relevant evaluations such as the IPCC 5th assessment report[29] and the Impact Assessments of the EU energy and climate policies. The ensemble of models includes computable general equilibrium models with detailed representation of economics sectors, technology-rich models, as well as hybrid models, thus collectively encompassing different modelling paradigms (see Methods for details). Three of the six models (IMAGE, MESSAGE-GLOBIOM and WITCH-GLOBIOM) have been directly involved in a recent quantification process of SSPs[1], and two models were identified as 'marker' models, that is, providing a preferred implementation of a selected SSP[19,20].

SSP narratives differ in many regards (see Supplementary Table 2 for a full description). In a nutshell, SSP 1, 2 and 3 describe a world characterized by low, medium and high challenges to mitigation and adaptation, respectively. Narratives are distinguished by variables that have been precisely quantified, such as population, and economic growth. Other variables—such as household preferences, technical progress, or technology availability—have been defined more qualitatively. For the sake of our analysis, we consider five main factors: population (POP), gross domestic product (GDP) per capita (GDPPC), energy intensity improvements (END), fossil fuel availability (FF) and low-carbon energy technology development (LC). These are the main family of drivers of emissions, commonly

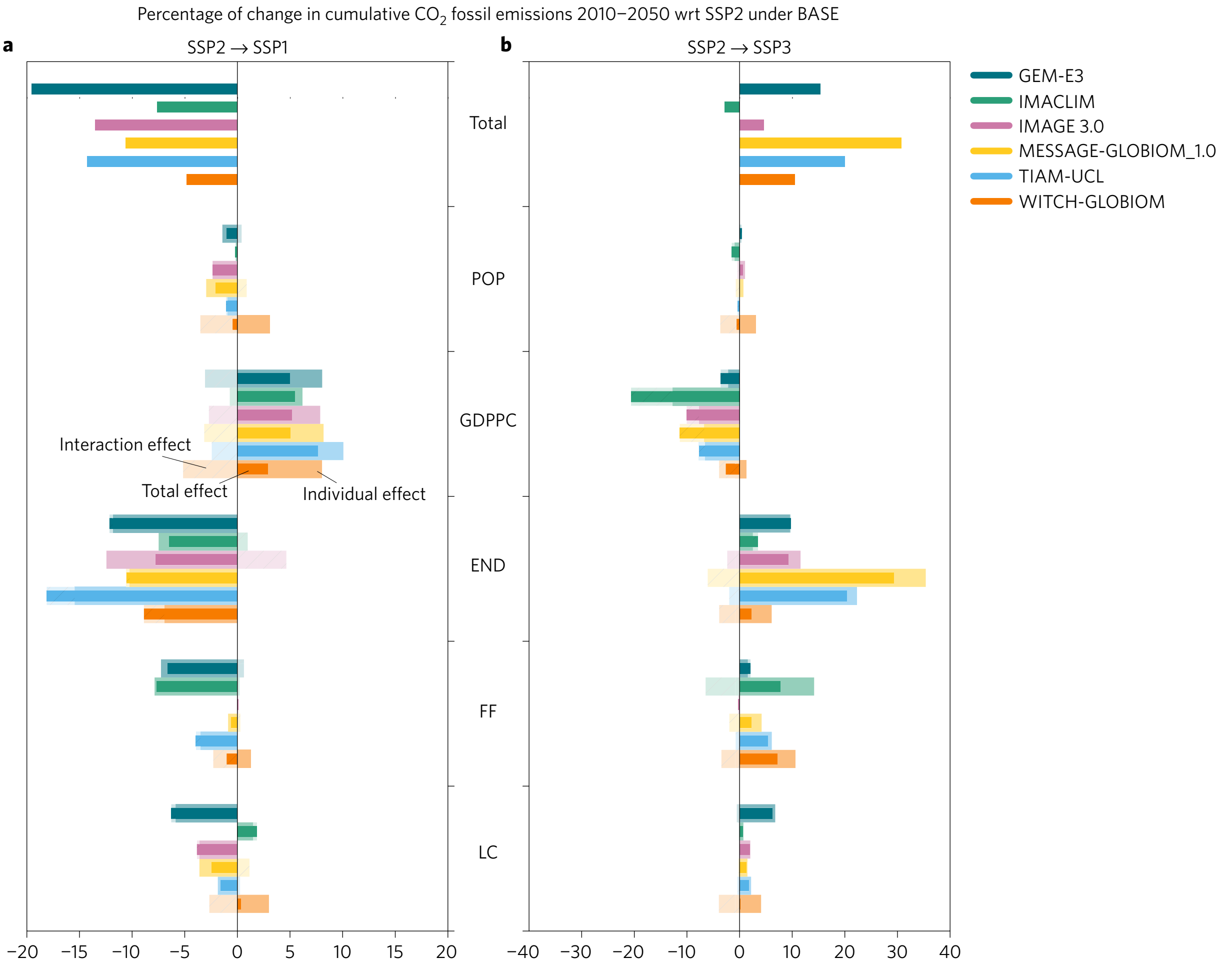

Figure 2 | Sensitivities of cumulative CO_2 emissions to scenario factors. a,b, Changes refer to global cumulative CO_2 FFI values in the period 2010–2050 when moving from SSP2 to either SSP1 (**a**) or SSP3 (**b**) without climate policies. TOTAL refers to total emission changes, and the rows below show emission changes for each of the five factors. Individual effects are reported with transparent thicker bars, total effects with solid thinner bars and interaction effects with striped bars. Values are reported for each of the six IAMs involved in the study.

used for historical decomposition analysis. The SSP assumptions for key variables related to these five drivers, as implemented in this study, are shown in Fig. 1.

Given this set-up, we have designed a scenario protocol such that when deviating from the central SSP2 case to either SSP1 or SSP3 it is possible to attribute the observed change in output to changes in each of these five groups of inputs. Since we are interested in determining also the relevance of parameter interactions, we employ a recently developed sensitivity analysis algorithm[2]. The method is illustrated in Supplementary Fig. 1, and involves changing the factor of interest from a reference to an alternative value, as well as changing all of the other factors except the one of interest. The first set of model runs provides the individual effect. The second—with a change in sign—gives us the total effect of that same factor, that is, an effect that contains both the individual effect and the interaction effect. The interaction effect includes all the interactions of the factor at hand with all the other factors. It is computed as the difference between individual and total effects. We coordinated the work in such a way that the six IAMs ran exactly on the same grid of points. The full matrix of scenarios is reported in Supplementary Table 4. The design has been chosen to obtain interaction effects with a parsimonious number of model evaluations, an important feature given the computational cost of the experiment.

Each of the six IAMs ran the 23 required scenarios for the no climate policy case (referred to as BASE), as well as another 23 scenarios for an idealized climate policy case (referred to as CPRICE). The climate policy scenarios assume a global carbon price starting in the year 2020 at 2005US\$11 per tCO_2eq, and rising at a fixed rate of 5% per year[30]. This is roughly consistent, at the global level, with a reasonable continuation of the climate stringency of current NDCs, but probably not with a 2 °C target (see Supplementary Information). Running both cases allows us to test whether the key parameters driving emissions are the same with and without a mitigation policy.

The main results of the sensitivity analysis of emissions for the no climate policy case and the first half of the century are shown in Fig. 2. The left-hand-side panel reports results when moving all drivers from the parameterization of the SSP2 scenario, the 'middle of the road', to those of SSP1, the more sustainable scenario. The overall reduction in emissions is 12% on average across models. GDP per capita and energy intensity improvement (GDPPC and END, respectively, in Fig. 2) appear to be the most important drivers, with an absolute median impact on emissions of 5% (full model range: 3 to 8%) and 10% (6 to 18%), respectively. Since SSP1 portrays a wealthier but more efficient world than SSP2, these two drivers induce variations in output of opposite sign and thus partly offset each other. Low availability of fossil fuel resources (FF) and high deployment of low-carbon technologies (LC) contribute to lowering SSP1 emissions with respect to SSP2 by 2% (−0.1 to 8% and −1.9 to 6%, respectively). Assumptions about population appear to have the lowest impact on emissions to 2050 across all models, with a median reduction of 1%. This is both due to models being

Table 1 | Changes in total sensitivities across climate policies and time horizons.

Year	2010–2050		2050–2090	
Policy input	BASE	CPRICE	BASE	CPRICE
SSP2 → SSP1				
TOTAL	−12 [−20,−5]	−9 [−17,1]	−27 [−38,−21]	−20 [−47,−9]
END	−10 [−18,−6]	−8 [−18,−6]	−21 [−40,−8]	−30 [−63,−7]
GDPPC	5 [3,8]	5 [3,7]	12 [7,16]	13 [6,26]
FF	−2 [−8,0]	−1 [−7,1]	−5 [−23,0]	−1 [−18,3]
LC	−2 [−6,2]	0 [−6,3]	−4 [−16,3]	3 [−6,14]
POP	−1 [−2,0]	−1 [−2,0]	−5 [−12,−2]	−9 [−12,−2]
SSP2 → SSP3				
TOTAL	13 [−3,31]	9 [−5,31]	10 [8,35]	11 [−21,92]
END	9 [2,29]	7 [2,30]	24 [4,44]	19 [4,99]
GDPPC	−9 [−21,−3]	−9 [−20,−3]	−44 [−86,−35]	−56 [−170,−29]
FF	4 [0,8]	3 [−1,6]	17 [0,21]	0 [−7,10]
LC	2 [0,6]	2 [1,6]	4 [2,11]	2 [−10,15]
POP	0 [−1,1]	0 [−2,1]	1 [−5,8]	8 [−4,20]

Sensitivities are quantified as total effects of factors on global cumulative CO_2 FFI emissions for two climate policies (BASE or CPRICE) and two time horizons (2010–2050 or 2050–2090). Median values are reported along with model ranges (in brackets). The row 'TOTAL' refers to the total observed change in output. All figures are rounded to the nearest whole number.

generally less responsive to changes in population than in other factors (Supplementary Fig. 13), and to population assumptions being only gradually diverging over time across SSPs (Fig. 1).

Figure 2 reports both individual and interaction effects that sum up to the total effect. The interaction effect can either amplify or dampen the changes resulting from individual effects. The assumptions of higher sustainability in SSP1 are synergistic with the availability of higher wealth per person, leading to a lower emission increase than the one produced by the same increase in income in the less sustainable SSP2 scenario. As a result, the median impact of larger income per capita on emissions is reduced from 8%—had we changed the factor in isolation—to 5%. For other parameters, the direction of individual and interaction effects is less clearcut, showing model-dependent behaviours.

The right-hand-side panel of Fig. 2 reports results when moving all scenario drivers from SSP2 to the more challenging world of SSP3. Emissions increase, in line with the SSP3 narrative, but variations across models are larger than between SSP2 and SSP1. Once again, income and energy efficiency emerge as key determinants. The magnitude of sensitivity to these two drivers is even larger than for the SSP1 case. Specularly to the SSP1 case, we find that interaction effects amplify the emission reductions associated with the GDP decrease from SSP2 to SSP3, and mitigate the increase in emissions associated with higher energy end use. On the one hand, income reduction in a more energy- and fossil-intensive economy leads to a larger drop in emissions. On the other, lower efficiency in a poorer world yields a smaller increase in emissions. Absolute levels of cumulative emissions and total effects in $GtCO_2$ can be found in Supplementary Fig. 8.

Table 1 provides a robustness test over different time horizons (that is, first and second halves of the century) and for the carbon price case. Overall, results are consistent across scenarios. In the medium term, that is, up to 2050, the results shown in Fig. 2 are confirmed in the case of the carbon price policy. Looking at the second half of the century, fossil fuel availability becomes slightly more important, while the contribution from low-carbon technologies availability and population remains marginal. Full tornado plots with values per model are reported in Supplementary Figs 9 (CPRICE 2050) and 11 (BASE 2090). Changes in sensitivities are further highlighted in Supplementary Figs 10 and 12.

This analysis has shown that the assumptions about energy demand and per capita income underlying the SSPs appear to be the most influential factors in explaining the projected change in future cumulative CO_2 emissions. Results are conditional to the width of uncertainty spanned by SSP storylines (for example, the expected limited variation in population in demographic projections in general up to 2050 reduces automatically its impact), the specific modelling choices in implementing the storylines and the different modelling responses. Normalizing sensitivities by the magnitude of drivers yields slightly different rankings, with resource and technology assumptions gaining importance (in Supplementary Fig. 13). The ranking of drivers is also affected by the fact that individual impacts of input groups can be dampened or reinforced when these are varied together.

Further research is needed to cast light on the mechanics of interactions and on the correlations between deviations from means and specific models characteristics. Expanding the analysis to additional factors, such as land-use emissions and carbon capture and storage, could provide additional insights. Results shown in this paper could be robust to these additional elements given that they play a significant role only in climate mitigation scenarios, but further exploration is warranted. Assessments aiming at quantifying uncertainty, exploring surprise scenarios[31], and designing hedging strategies in the face of both parametric and model uncertainty[32] are needed to inform climate policy, including the upcoming reports of the IPCC. Such efforts, along with those undertaken in this paper, can provide important insights into the nascent literature on IAMs diagnostics[30]. In addition to unpacking model results, it can also provide guidance in terms of research directions: our results on the relevance of energy intensity together with the recognition of the currently limited capability to model energy demand[33] indicate this as a focus of priority for future model development.

Methods

Methods, including statements of data availability and any associated accession codes and references, are available in the online version of this paper.

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Author contributions

G.M., M.T., V.B. and E.Ó. designed the experiment. All authors contributed to the final design, implemented the scenarios and provided model output data. G.M. performed the sensitivity computations. G.M. and M.T. wrote the first draft of the paper. All authors contributed to the final writing of the paper.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to G.M.

Competing financial interests

The authors declare no competing financial interests.

Methods

Socioeconomic pathways. The narratives behind the SSP scenarios[7–10] have been described both qualitatively[11] (see Supplementary Table 2) and, more recently, also quantitatively[1,34]. This study focuses just on the first 3 SSPs[19–21], which, if located in a mitigation versus adaptation challenge space, would belong to the main diagonal, as both types of challenge increase.

SSPs are different along many dimensions, which eventually translate into different assumptions on CO_2 emissions drivers (Supplementary Figs 2–4). Here we assume that SSP scenarios are implemented by changing model inputs belonging to one of the five categories described below.

POP refers to assumptions on regional population over the century. Estimates have been developed by the International Institute for Applied Systems Analysis (IIASA) at country level[35]. SSP1 has lower global population growth, while in SSP3 the growth is low in industrialized and high in developing countries, resulting in higher global levels.

GDPPC refers to assumptions on regional income per capita over the century. These are obtained by dividing the GDP level projections obtained with the ENV-Growth model by OECD (Organisation for Economic Co-operation and Development) specialists for the SSP scenarios[36] with the population levels above. SSP1 features favourable economic growth, while the SSP3 economy is weakened by international fragmentation.

END refers to assumptions on energy intensity. Qualitatively, SSP1 features a fast phase-out of traditional fuels, modest service demands and low energy intensity of services and industry due to improved resource efficiency. SSP3 goes in the opposite direction, with continued reliance on traditional fuels, high service demands and high energy intensity of services. Quantitatively, levels of world final energy demand per unit of GDP were aligned across models and scenarios with the same END assumptions.

FF refers to assumptions on fossil fuel availability. Qualitatively, SSP1 features a fast decrease in fossil fuel dependency, reluctance to use unconventional fossil resources, slow extraction technology improvements and no trade barriers. SSP3 instead involves supportive policies to the production of both conventional and non-conventional fossil fuels, with a medium to high development of extraction technology, partially counterbalanced by high trade barriers and support of energy security goals. Quantitatively, levels of world fossil primary energy per unit of primary energy were aligned across models and scenarios with the same FF assumptions.

LC refers to assumptions on low-carbon energy technologies availability. Qualitatively, SSP1 features high development and high social acceptance of non-biomass renewables, specifically wind and solar technologies, along with a medium development and low social acceptance of nuclear. On the other side, SSP3 involves low development and medium social acceptance of non-biomass renewables, along with low to medium development and high social acceptance of nuclear. Quantitatively, levels of world renewables and nuclear primary energy per unit of primary energy were aligned across models and scenarios with the same LC assumptions.

More details on the implementation in the six models of these five sets of assumptions across the three SSP scenarios can be found in Supplementary Table 3. These sets are referred to as sensitivity 'factors', as each represents a collection of related scenario features relevant to the sensitivity, or emissions 'drivers', for their important role in shaping emissions.

Elements related to land use and CCS are left out from this analysis. The assumption is to leave them unchanged at their SSP2 levels. Thus, in principle a scenario with all five input categories at level 1 may slightly differ in terms of fossil fuel CO_2 emissions from an SSP1 scenario with its comprehensive implementation.

Finite change sensitivity analysis and design of experiment. In our analysis, we assume that CO_2 emissions Y are an output of a set of model inputs $\boldsymbol{z}$ given by the model $f(\boldsymbol{z})$. These inputs are grouped into a limited number N of categories, or sensitivity factors. When changing one of our N factors, for example, POP assumptions from SSP2 to SSP1 levels, we are changing the corresponding subset of $\boldsymbol{z}$ components, for example, regional population levels at each time period.

In decomposition analysis, often a simple relationship between model drivers and output is postulated (for example, a product or a sum of products). This allows subsequently to estimate the influence of individual factors using an index decomposition analysis (for example, with logarithmic mean Divisia index or LMDI[37]). Such an approach is useful especially when no additional information exists (for example, for historical data or for a limited set of model outputs).

In our case, CO_2 emissions are the result of an arbitrarily complex computation, represented by each model f. Since we have access to the data-generating process, we can build a convenient data set of pairs $(\boldsymbol{z}, Y)$ for our sensitivity purposes. For further information on the difference with an LMDI approach, refer to the Supplementary Information.

We resort to a finite change sensitivity method based on the functional ANOVA expansion. A change ΔY in output, obtained when moving from a reference scenario 0 with inputs $\boldsymbol{z}^0$ to a deviation scenario 1 with inputs $\boldsymbol{z}^1$ is expanded in a sum of N individual and $2^N - N$ interaction terms.

The individual term ϕ_i^1 for a factor i is the ΔY obtained when moving the components of $\boldsymbol{z}$ related to factor i from levels 0 to levels 1. The interaction term $\phi_{i,j}^1$ for the factors i and j is the ΔY obtained when moving the components of $\boldsymbol{z}$ related to that pair of factors from levels 0 to levels 1, minus the sum of i and j individual effects, that is, $\phi_i^1 + \phi_j^1$. Analogous definitions can be thought for interaction terms involving three or more factors, every time subtracting effects of lower order. If we sum all the terms involving a factor i, we obtain the total effect ϕ_i^T of i. This represents the impact of changing factor i on the output, accounting for all the interactions embodied in f.

Thanks to a computational shortcut, it is possible to reduce the number of scenarios required for calculating total effects from exponential to linear[2,38], at the expense of ignoring each single interaction term. ϕ_i^T is in fact equivalent to the opposite of the ΔY obtained when moving all the inputs corresponding to all the factors but i from 0 to 1. This is illustrated in Supplementary Fig. 1, and the resulting scenario matrix required for calculating the sensitivities is shown in Supplementary Table 4. In Supplementary Information the methodology is further described in rigorous terms.

Integrated assessment models. The sensitivity analysis was repeated with six well-established global climate–energy–economy models. The model suite used in this paper spans the major families of IAMs: general versus partial equilibrium, bottom up versus top down, sectoral versus technological disaggregation, and simulation versus optimization. This provides useful information on how robust the results are to model uncertainty. All these models have been leading contributors of scenarios to international assessments (for example, IPCC AR5 scenario database), as well as EU policy evaluation. A brief description of the models follows.

GEM-E3-ICCS[24] is a computable general equilibrium model that puts emphasis on: the analysis of market instruments for energy-related environmental policy, such as taxes, subsidies, regulations, emission permits and so on, at a degree of detail that is sufficient for national, sectoral and worldwide policy evaluation; the assessment of distributional consequences of programmes and policies, including social equity, employment and cohesion for less developed regions.

IMACLIM[26] is a recursive dynamics hybrid model, combining a general equilibrium approach with technology-explicit modules. It is intended to study the interactions between energy systems and the economy, to assess the feasibility of low-carbon development strategies and the transition pathway towards low-carbon future.

IMAGE[25] is a recursive dynamics model that can be described as a geographically explicit assessment, integrated assessment simulation model, focusing on a detailed representation of relevant processes with respect to human use of energy, land and water in relation to relevant environmental processes. The model aims: to analyse interactions between human development and the natural environment to gain better insight into the processes of global environmental change; to identify response strategies to global environmental change based on assessment of options; and to indicate key interlinkages and associated levels of uncertainty in processes of global environmental change.

MESSAGE-GLOBIOM[20,39] integrates the energy-engineering model MESSAGE and the land-use model GLOBIOM into a consistent integrated assessment framework. To account for general equilibrium effects MESSAGE-GLOBIOM also soft-links to the aggregated macroeconomic model MACRO.

TIAM-UCL[27] is an energy-systems-focused partial-equilibrium model. It uses the TIMES modelling platform, extended with a stylized representation of non-energy emissions and a simple climate module. Scenario-based simulations maximize the total discounted sum of consumer and supplier surplus over the model horizon, while taking into account the constraints (for example, energy demand to be fulfilled, availability of energy resources and so on).

WITCH-GLOBIOM[28] is a hybrid economic optimal growth model, including a bottom-up energy sector and a simple climate model, embedded in a game theoretic set-up. It evaluates the impacts of climate policies on global and regional economic systems and provides information on the optimal responses of these economies to climate change. It also considers the positive externalities from learning by doing and learning by researching in the energy-related technological change.

Some key characteristics of the six models are reported in Supplementary Table 1. Additional information can be found online at http://themasites.pbl.nl/models/advance/index.php, especially regarding the technological detail in representing the energy sector. Supplementary Table 3 illustrates how the five sensitivity factors were incorporated in the different models.

Climate policies. The sensitivity analysis is performed twice, one for each of the following climate policies: BASE, with a global carbon price equal to 0; CPRICE, with a global carbon price equal to 2005US$30 per tCO_2eq in 2040, starting in 2020 and increasing at 5% yr^{-1}.

The CPRICE climate policy adopts a similar carbon price to one of the diagnostic carbon prices recommended by the Integrated Assessment Modeling Consortium[30]. Further information on how this diagnostic CPRICE scenario compares with the more familiar NDC and 2° scenarios, both in terms of cost of carbon and resulting emissions, as well as the difference in emissions between SSPs, can be found in the Supplementary Information.

Data availability. The sensitivity computations in this study are based on the data collected on future global CO_2 FFI emissions across all models and scenarios, which are available within the Supplementary Information. All the other variables collected in this exercise and relevant to reproduce both main and supplementary figures are included as well. Official SSP marker data can be found online at https://secure.iiasa.ac.at/web-apps/ene/SspDb. Further information regarding the code used and the data produced are available from the corresponding author on request.

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