Scenario modelling of the sustainable development goals under uncertainty

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Abstract

The future uncertainty and complexity of alternative socioeconomic and climatic scenarios challenge the model-based analysis of sustainable development. Obtaining robust insights requires a systematic processing of uncertainty and complexity not only in input assumptions, but also in the diversity of model structures that simulates the multisectoral dynamics of human and Earth system interactions. Here, we implement the global change scenarios, i.e., the Shared Socioeconomic Pathways and the Representative Concentration Pathways, in a feedback-rich, integrated assessment model of system dynamics to explore the impacts of model uncertainty and structural complexity on the projection of these scenarios for sustainable development. Our modelling shows internally consistent scenario storylines across sectors, yet with quantitatively different realisations of these scenarios compared to other models. It also demonstrates the sensitivity of sustainability trajectories related to food and agriculture, well-being, education, energy, economy, sustainable consumption, climate, and biodiversity conservation to the modelled scenarios, driven by the complex and uncertain multisectoral dynamics underlying the SDGs. The results highlight the importance of enumerating global change scenarios and their uncertainty exploration with a diversity of models of different input assumptions and structures to capture a wider variety of future possibilities and sustainability indicators.

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Diversifying models for analysing global change scenarios and sustainability pathways

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Non-Technical Summary

Models are increasingly used to inform the transformation of human-Earth systems towards a sustainable future, aligned with the Sustainable Development Goals (SDGs). We argue that a greater *diversity of models* ought to be used for sustainability analysis to better address complexity and uncertainty. We articulate the steps to model global change socioeconomic and climatic scenarios with new models. Through these steps, we generate new scenario projections using a human-Earth system dynamics model. Our modelling brings new insights about the sensitivity of sustainability trends to future uncertainty and their alignment with or divergence from previous model-based scenario projections.

Technical Summary

The future uncertainty and complexity of alternative socioeconomic and climatic scenarios challenge the model-based analysis of sustainable development. Obtaining robust insights requires a systematic processing of uncertainty and complexity not only in input assumptions, but also in the diversity of model structures that simulates the multisectoral dynamics of human and Earth system interactions. Here, we implement the global change scenarios, i.e., the Shared Socioeconomic Pathways and the Representative Concentration Pathways, in a feedback-rich, integrated assessment model of human-Earth system dynamics, called FeliX, to serve two aims: (1) to provide modellers with well-defined steps for the adoption of established scenarios in new integrated assessment models; (2) to explore the impacts of model uncertainty and its structural complexity on the projection of these scenarios for sustainable development. Our modelling shows internally consistent scenario storylines across sectors, yet with quantitatively different realisations of these scenarios compared to other integrated assessment models due to the new model's structural complexity. The results highlight the importance of enumerating global change scenarios and their uncertainty exploration with a diversity of models of different input assumptions and structures to capture a wider variety of future possibilities and sustainability indicators.

Social Media Summary

New study highlights the importance of global change scenario analysis with new, SDG-focused integrated assessment models

Keywords

Scenario, Integrated assessment, System dynamics, SDGs, Sustainability, Uncertainty.

1 Introduction

The 17 Sustainable Development Goals (SDGs) under the United Nations 2030 Agenda for Sustainable Development represent global ambitions for achieving economic development, social inclusion, and environmental stability (UN, 2015). Progressing towards the diverse and ambitious SDGs requires compromising between competing sustainability priorities and harnessing synergies over deeply uncertain, long-term futures (Bandari *et al.*, 2021; Pradhan *et al.*, 2017). To assist in reasoning and planning, computer models and simulations, referred to as integrated assessment models (IAMs) (van Beek *et al.*, 2020), models of multisector dynamics (Jafino *et al.*, 2021), or transitions models (Köhler *et al.*, 2018; Moallemi & de Haan, 2019), have been effectively used to systematically analyse the interactions of conflicting, inter-connected sustainability priorities in integrated human-Earth systems (Calvin & Bond-Lamberty, 2018) and to navigate actionable compromises between competing agendas (Gold *et al.*, 2019). These modelling efforts aim to advance the understanding and analysis of integrated human-Earth system co-evolution over time by bridging sectors, and support societal transformation planning through computational analysis.

A diverse set of models has been used to inform sustainable development (Verburg *et al.*, 2016), including input-output models (Wiedmann, 2009), macro-economic and optimisation models (DeCarolis *et al.*, 2017), computational general equilibrium models (Babatunde *et al.*, 2017), system dynamics models (Moallemi *et al.*, 2021; Pedercini *et al.*, 2019), and bottom-up agent-based models (Hansen *et al.*, 2019). Modelling applications have spanned different aspects of the SDGs such as food and diet (Bijl *et al.*, 2017; Eker *et al.*, 2019), climate adaptation (JGCRI, 2017; Mayer *et al.*, 2017; Small & Xian, 2018), land-use (Doelman *et al.*, 2018; Gao & Bryan, 2017), energy (Rogelj *et al.*, 2018a; Walsh *et al.*, 2017), transportation (Moallemi & Köhler, 2019), and biodiversity conservation (Mace *et al.*, 2018). Models have also assessed the nexus of (often limited) interacting SDGs (Randers *et al.*, 2019) such as food-energy-water (Van Vuuren *et al.*, 2019), land-food (Gao & Bryan, 2017; Obersteiner *et al.*, 2016), and land-food-biodiversity (Leclère *et al.*, 2020), amongst others. Model-based analysis of sustainable development over long timescales is, however, challenged by the conjunction of deep uncertainty around future global socioeconomic and climatic conditions and the complexity of integrated human-Earth system response under these uncertain conditions.

To address these challenges, past studies have often used *scenarios* to explore the plausible trajectories of system behaviour according to different sets of assumptions about the future (Guivarch *et al.*, 2017; Moss *et al.*, 2010; Trutnevyte *et al.*, 2016). Within the context of climate change and sustainability science, the Shared Socioeconomic Pathways (SSPs) (O'Neill *et al.*, 2017; Riahi *et al.*, 2017) and the Representative Concentration Pathways (RCPs) (Meinshausen *et al.*, 2020; van Vuuren *et al.*, 2011), have dominated scenario studies over the past decade (O'Neill *et al.*, 2020). They project futures based on different challenges to mitigation and adaptation through five possible socioeconomic pathways (SSPs 1 to 5) and five different greenhouse gas emissions trajectories (RCPs 1.9, 2.6, 4.5, 6.0, 7.0, 8.5) (see Subsection 2.3). The future developments of energy, land-use, and emissions sectors according to the SSPs and RCPs have been extensively characterised and expanded, using a set of five so-called *marker* integrated assessment models including IMAGE (Bouwman *et al.*, 2006; van Vuuren *et al.*, 2017), MESSAGE-GLOBIOM (Fricko *et al.*, 2017), AIM (Fujimori *et al.*, 2017), GCAM (Calvin *et al.*, 2017), and REMIND-MAGPIE (Kriegler *et al.*, 2017). The research community has frequently used the global SSP and RCP scenarios with these marker models in climate impact assessments (Rogelj *et al.*, 2018a) and for analysing other Earth system processes (e.g., biodiversity (Leclère *et al.*, 2020); see O'Neill *et al.* (2020) for a review).

Despite past successful efforts, there are still important limitations to address for increasing the impact and usefulness of global change scenario frameworks. One major gap is that the application of the SSPs and RCPs to areas beyond climate change, such as sustainable development, has been so far limited. There are only few studies that have extended these scenario frameworks to the evaluation of the SDGs (van Soest *et al.*, 2019). Among these, *The World in 2050* (TWI2050, 2018) and the assessment of sustainable development pathways (Soergel *et al.*, 2021) are the prominent examples, both mostly replying on the marker integrated assessment models as their simulation engine. The broader use of SSPs and RCPs for sustainable development is crucial for developing a more comprehensive account of possible integrated futures and more diverse response options across connected global challenges (O'Neill *et al.*, 2020).

Another noticeable gap is that most of the past SSP-RCP projections were based on the assumptions of five original marker models, and the use of new, *non-marker* integrated assessment models with different sets of input and structural assumptions has been rare. Among the few applications of non-marker models is Allen *et al.* (2019) who used four SSPs as benchmarks to guide the development of national-scale scenarios, based on inequality and resource-use intensity, to assess scenarios of progress towards the SDGs for Australia. The adoption of non-marker, emerging models, with different sectoral boundaries (e.g., water (Graham *et al.*, 2018), diet change (Eker *et al.*, 2019)) and levels of structural complexity (e.g., system dynamics models (Walsh *et al.*, 2017)), is important to expand the scenario space around SSPs and RCPs with a wider set of futures and also to project a larger diversity of sustainability indicators aligned with the SDGs (O'Neill *et al.*, 2020).

These current limitations signify the need for a more diverse quantification of global reference scenarios (e.g., SSPs, RCPs) with new integrated assessment models (Jaxa-Rozen & Trutnevyte, 2021) and in new domains such as sustainable development. Addressing this need has become more important in recent years especially given the increasing demand for model-based SDG analysis (Allen *et al.*, 2019; Pedercini *et al.*, 2019; Soergel *et al.*, 2021) and the emergence of new, open-source integrated assessment models (e.g., FeliX (Walsh *et al.*, 2017), iSDGs (Pedercini *et al.*, 2019), Earth3 (Randers *et al.*, 2019), see a review in Duan *et al.* (2019)) that are simpler yet have a broader scope compared to the marker models (Riahi *et al.*, 2017), sufficient to address several SDGs.

Here, we implement and explore global SSP and RCP scenario frameworks and their uncertainty with a feedback-rich system dynamics model for sustainable development, called the Functional Enviro-economic Linkages Integrated neXus (FeliX) (Eker *et al.*, 2019; Walsh *et al.*, 2017). This, first of all, provides modellers with well-defined steps for the adoption of established global change scenarios in their new modelling works with a clear demonstration of these steps' implementation in FeliX (Section 2). Second, it provides a new analysis of global trajectories of the five plausible combinations of SSPs and RCPs under 50,000 different realisations (Section 3). These results show how socioeconomic and climate drivers could unfold in the future through the multi-sectoral dynamics of demography, economy, energy, land, food, biodiversity, and climate systems (Subsection 3.1) and in what areas and to what extents they diverge from previous projections (Subsection 3.2). The results also show the impacts across 16 sustainability indicators representing eight SDGs related to agriculture and food security (SDG2), health and well-being (SDG3), quality education (SDG4), clean energy (SDG7), sustainable economic growth (SDG8), sustainable consumption and production (SDG12), climate action (SDG13), and biodiversity conservation (SDG15) (Subsection 3.3). Our results highlight the value added of exploring the implications of new models for global scenarios and provide insights into the global trajectories towards several SDGs under a larger scenario space (Section 4).

2 Methods

We used a non-marker integrated assessment model of sustainable development (Step 1). We identified the model's influential parameters for the generation of global scenarios (Step 2). We elaborated our scenario assumptions and set up the model under these assumptions (Steps 3 and 4). We then explored the uncertainty space of implemented scenarios in the model using exploratory modelling (Step 5). We let the model, with its new structural complexity, generate the diversity of output behaviours, explored various quantifications of global reference scenarios outside their standard projections, and analysed diversions from other models and implications for the SDG analysis (Step 6). Each step is explained in detail as follows (Figure 1).

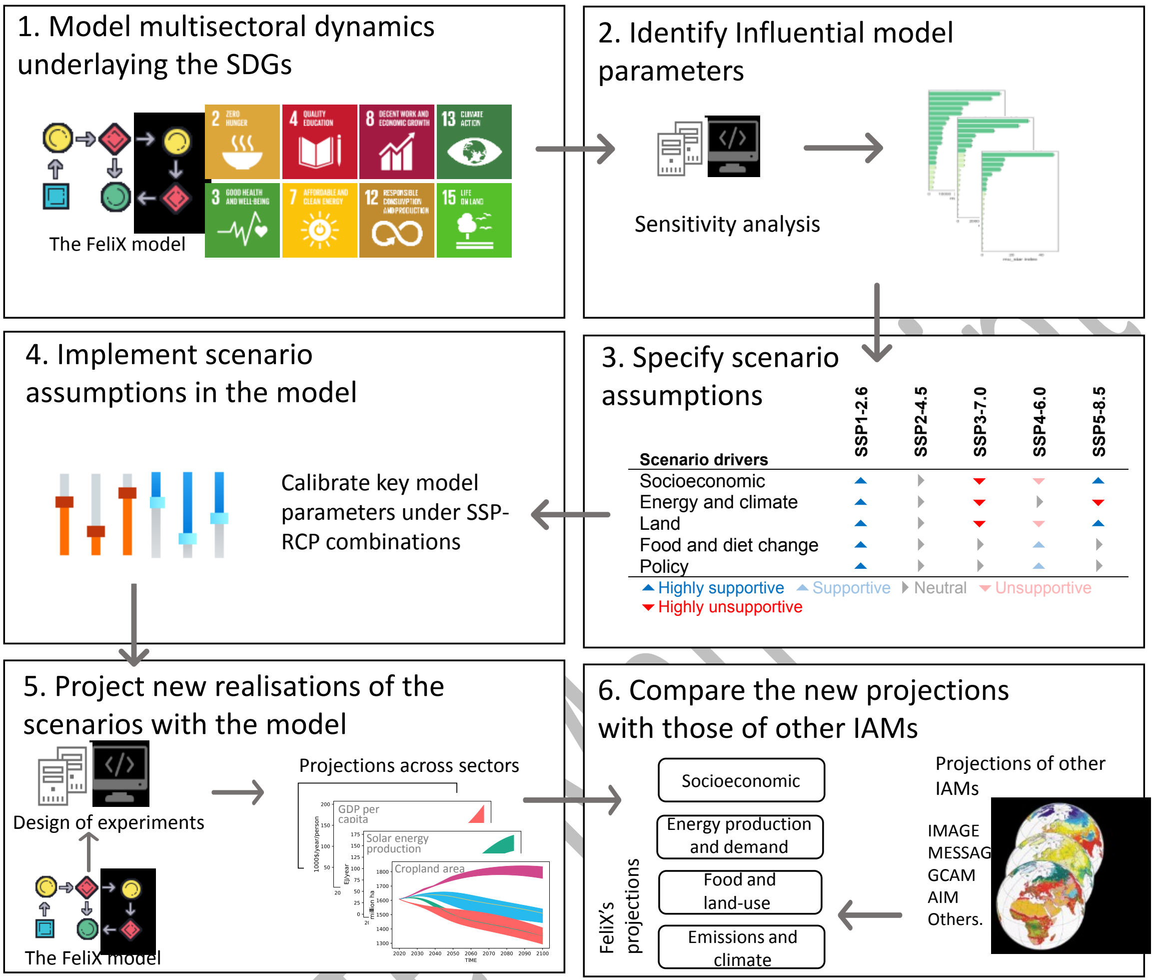

Figure 1. Overview of methodological steps for implementing global scenario frameworks in a new integrated assessment model for sustainable development.

2.1 Model multisectoral dynamics underlying SDGs

We modelled anthropogenic processes of the multisectoral dynamics that drive SDG progress through an integrated assessment model of human and Earth system interactions called FeliX (Figure 2). The human system sub-models capture socioeconomic dynamics and human decision-making (e.g., demography, education, economy, land-use change) and the Earth system sub-models capture biogeophysical processes (e.g., climate, carbon cycle, phosphorus and nitrogen cycles). FeliX simulates complex feedback interactions between these human and Earth systems sub-models. The integration of feedbacks in FeliX enhances the understanding of reasons for non-linearities and radical change that emerge in sustainability pathways from the co-development of human activities and environmental change. FeliX's feedback-rich structure makes this model stand out among most global models that miss (or simplify) the important two-way feedback interactions between various sectors by primarily focusing on specific sectors (e.g., food (Willett *et al.*, 2019), land-food (Obersteiner *et al.*, 2016), food-energy-water (Van Vuuren *et al.*, 2019)) or only a one-way information exchange from socioeconomic factors to climatic, biophysical processes (van Vuuren *et al.*, 2012).

FeliX is based on the system dynamics approach (Moallemi *et al.*, 2021; Sterman, 2000) with a resolution set at a global scale and with annual timescale over a long-term period (1900-2100). The model has been used as a policy assessment tool in exploring emissions pathways (Walsh *et al.*, 2017), evaluating sustainable food and diet shift (Eker *et al.*, 2019), and analysing socio-environmental impacts in Earth observation systems (Rydzak *et al.*, 2010). The model outputs have been also tested and validated against historical data from 1900 to 2015 across all sub-models, available in the extended model documentation in Rydzak *et al.* (2013) as well as in Walsh *et al.* (2017) and Eker *et al.* (2019).

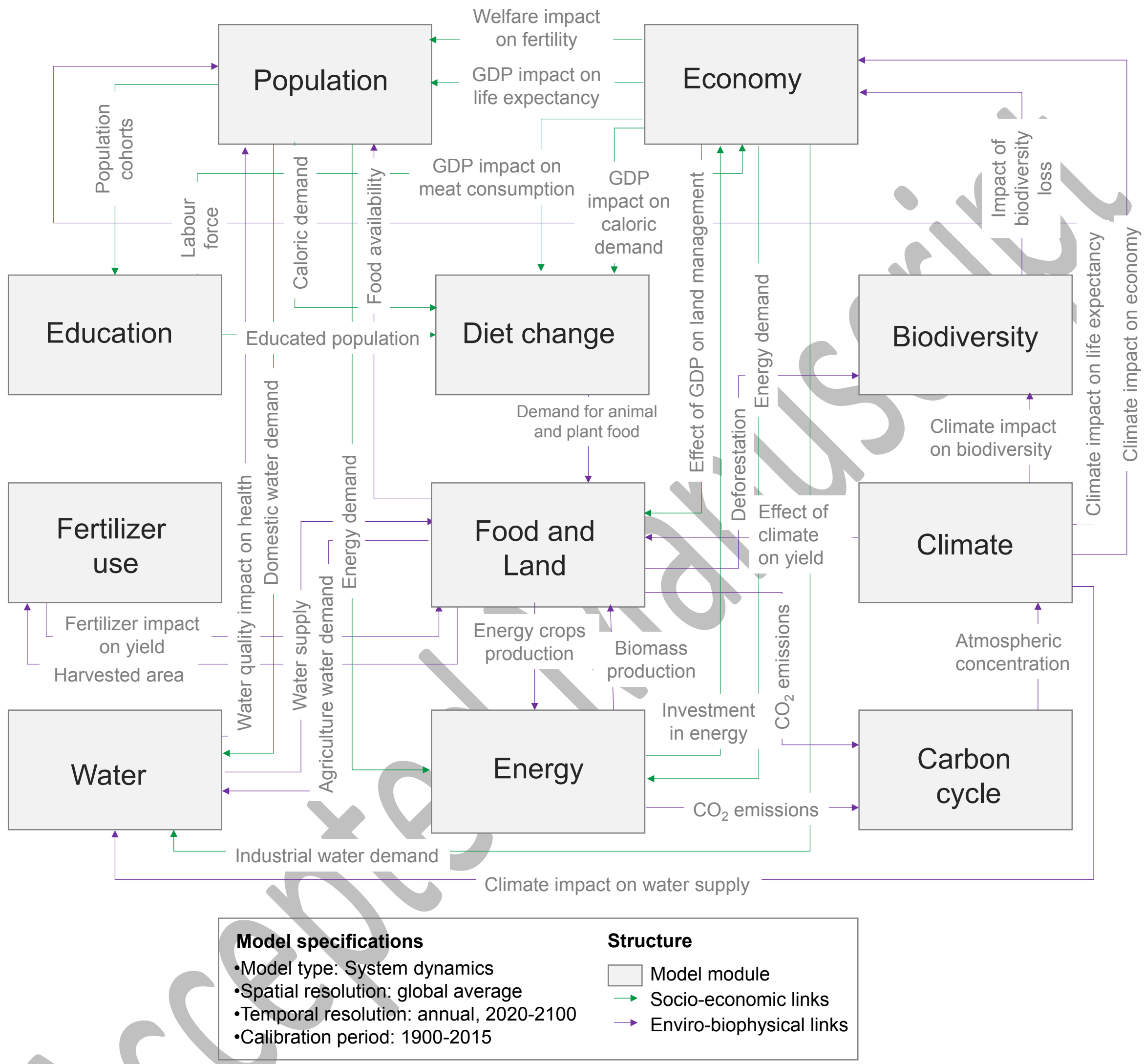

Figure 2. The overview of the FeliX model. Adapted from and updated based on Rydzak *et al.* (2013). See Supplementary Methods for the description of each sub-model.

Using FeliX, we modelled 16 indicators across eight societal and environmental SDGs (Table 1). The selection of SDGs and their indicators was guided by the model scope with the aim of covering a wider diversity of sustainable development dimensions as in previous studies (Allen *et al.*, 2019; Gao & Bryan, 2017; Obersteiner *et al.*, 2016; Pedercini *et al.*, 2019; Randers *et al.*, 2019; van Vuuren *et al.*, 2015). The SDGs and their indicators were implemented across the 11 FeliX's sub-models of population, education, economy, energy, water, food and land, fertiliser use, diet change, carbon cycle, climate, and biodiversity (see each sub-model description in Supplementary Methods). Each sub-model includes feedback interactions between several model components necessary to generate complex interactions underlying the SDGs.

This feedback-rich nature and flexibility of the FeliX model also enables exploring the impacts of tipping mechanisms on sustainability pathways. Climate tipping elements that can exacerbate warming (Lenton *et al.*, 2008), such as permafrost melting and the loss of Amazon rainforest, can be explicitly included in the model to explore the safe pathways of human actions to avoid such tipping points. Similarly, social tipping dynamics (Otto *et al.*, 2020) that accelerate mitigation actions can be explored using the FeliX model and the SDG framework. Several feedback mechanisms underlying possible social tipping dynamics, such as the change of norms, impact of education and learning effects in the energy system are already included in the model scope, hence in our analysis below. Future work can extend the FeliX model and investigate the compound dynamics of climate and social tipping elements.

Table 1. The list of modelled SDG indicators. There are two modelled indicators under each SDG for consistency. Each indicator trajectory is simulated in the model based on the interaction of multiple sectors. This underlying sectoral dynamic for each indicator is specified in the last column.

Indicator	Description	Desired progress	Underlying sectoral dynamics
SDG 2. End hunger, achieve food security, and promote sustainable agriculture			
Cereal Yield (tons $year^{-1}$ ha^{-1})	The annual production rate per hectare of harvested croplands dedicated to grains production.	Improve the productivity of the croplands for cereal yield production.	Land, food/diet, water, climate, economy
Animal Calories (kcal $capita^{-1}$ day^{-1})	The total annual production of pasture-based meat and crop-based meat - excluding seafoods - per person per day.	Meet the increasing global demand for food with less meat consumption.	Land, food/diet, water, population, education, economy, climate
SDG 3. Ensure healthy lives and promote well-being for all at all ages			
Human Development Index (-)	The UNDP average of three indices of income, health, and education that affect human capabilities to sustain well-being.	Advance human wellbeing and richness of life.	Education, economy, population, food/diet, climate, biodiversity
Adolescent Fertility Rate (person $year^{-1}$ $1000women^{-1}$)	The number of births per 1,000 by women between the age of 15-19. This is a negative indicator, i.e., the lower, the better.	Reduce childbirth by adolescent girls with improved sexual and reproductive healthcare.	Education, economy, population
SDG 4. Ensure inclusive and equitable quality education and promote lifelong learning opportunities			
Mean Years of Schooling (number of years)	Average number of completed years of primary, secondary, and tertiary education (combined) of population.	Increase educational attainments across population and in all levels.	Education, population
Population Age 25 to 34 with Tertiary Education (%)	The percentage of the population, aged between 25-34 years old, who have completed tertiary education.	Improve tertiary education coverage.	Education, population
SDG 7. Ensure access to affordable, reliable, sustainable and modern energy			
Share of Renewable Energy Supply (%)	Percentage of renewable (solar, wind, biomass) energy supply share in total energy production.	Increase the average global share of renewable energies in the final basket of total energy production.	Energy, economy, population
Energy Intensity of GWP (MJ $\$^{-1}$)	An indication of how much energy is used to produce one unit of economic output.	Reduce the energy intensity of services and industries per GDP.	Energy, economy, population
SDG 8. Promote sustained, inclusive and sustainable economic growth for all			
GWP per Capita ($1000 $person^{-1}$ $year^{-1}$)	Gross World Product, i.e., the global total GDP, divided by the global population.	Improve economic prosperity of all countries in an inclusive and sustainable way.	Economy, population, education, energy, climate, biodiversity
CO_2 Emissions per GWP (kg CO_2 $\$^{-1}$)	Human-originated CO_2 emissions stemming from the burning of fossil fuels divided by the unit of GDP.	Reduce carbon footprint of the growing economy.	Economy, population, climate, biodiversity, carbon cycle energy
SDG 12. Ensure sustainable consumption and production patterns			
Nitrogen Fertiliser Use in Agriculture (million tons N $year^{-1}$)	Commercial nitrogen fertiliser application in agriculture affected by land availability, income, and technology impact on fertiliser use.	Manage a fertiliser application to balance between declining soil	Land, food/diet, economy, population

Agri-Food Nitrogen Footprint (kg year^{-1} person^{-1})	Nitrogen (N) emissions to the atmosphere and leaching/runoff from commercial application in agriculture and with manure.	fertility and the risk of polluting nutrient surplus.	Land, food/diet, economy, population
SDG 13. Take urgent action to combat climate change and its impacts			
Atmospheric Concentration CO_2 (ppm)	Atmospheric CO_2 concentration per parts per million.	Significantly reduce global CO_2 emissions across sectors.	Population, economy, land, food/diet, energy, carbon cycle
Temperature Change from Preindustrial (degree °C)	Global annual mean temperature change from the pre-industrial time calculated as atmosphere and upper ocean heat divided by their heat capacity.	Limit global temperature change from preindustrial level.	Population, economy, land, food/diet, energy, carbon cycle
SDG 15. Protect, restore and promote sustainable use of terrestrial ecosystems and forests			
Forest to Total Land Area (%)	Percentage of forest to total (agricultural, urban and industrial, others) land areas.	Significantly reduce the current deforestation rates and restore degraded forest lands.	Land, population, economy, energy, food/diet
Mean Species Abundance (%)	The compositional intactness of local communities across all species relative to their abundance in undisturbed ecosystems.	Limit significantly the current rate of biodiversity extinction from anthropogenic activities.	Energy, climate, food/diet, land

2.2 Identify influential model parameters for scenario modelling

Integrated assessment models often have many demographic, macro-economic, techno-economic, and environmental parameters. However, among these parameters, some are more influential than others and some may have only trivial impacts on model behaviour. We identified influential parameters for scenario modelling from an initial list of 114 model parameters (Supplementary Table 2) and ranked them based on their impact (with non-linear interactions) on 20 model outputs using Morris elementary effects (Campolongo *et al.*, 2007; Morris, 1991). Morris elementary effects is a suitable global sensitivity analysis method for integrated assessment models with a large number of input parameters and a complex structure of nonlinear feedbacks where computational costs are very high. The method has proved to generate reliable sensitivity indices with a better computational efficiency compared to other techniques (Campolongo *et al.*, 2007; Gao & Bryan, 2016) (see sensitivity analysis details in Supplementary Methods).

Figure 3 shows the ranking and selection of influential model parameters to be used for scenario modelling of different sectors (e.g., population, GDP, energy demand, forest land cover) by 2030, 2050, and 2100. The identified model parameters were diverse enough to capture influential global change in relation to demographic (e.g., fertility rate, life expectancy), education (e.g., enrolment and graduation rates), economic (e.g., capital elasticity of the economy), and lifestyle (i.e., energy demand and diet change). A substantial variation was observed in the influence of various parameters. The top influential parameters were related to socioeconomic factors (demography, education, economy) and diet change, indicating them as key parameters underpinning scenario modelling. We also observed that the influential parameters did not change significantly over time (Figure 3). Therefore, we used the influential parameters based on their long-term sensitivity (by 2100) as our reference set of model parameters to work with for scenario modelling.

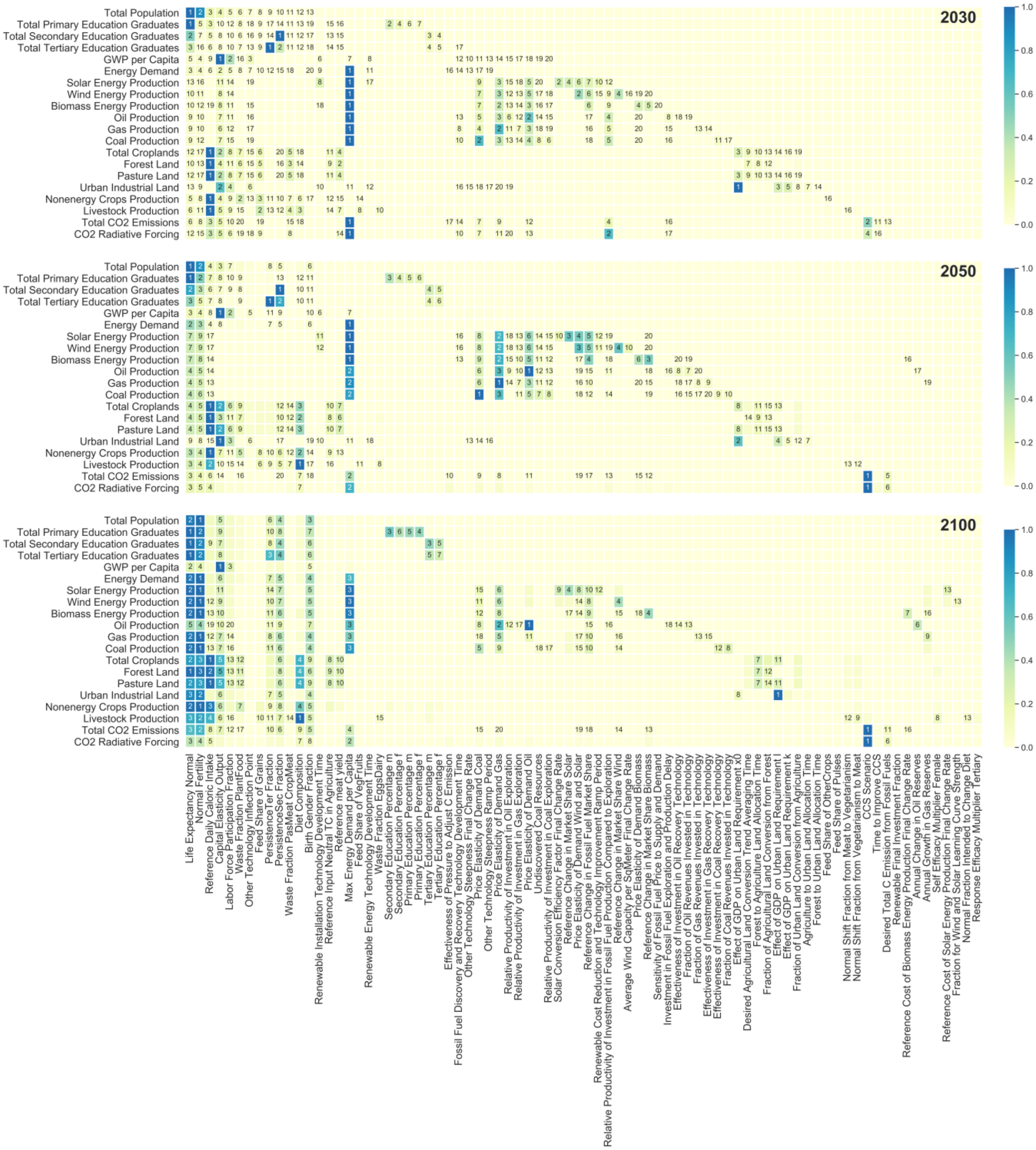

Figure 3. The ranking of influential model parameters. Sensitivity is the normalised values of Morris index μ^* between 0 and 1. For each output variable (y axis), the most influential input parameters (x axis) are annotated with their rank. Information on the unit and definition of each parameter is available in Supplementary Table 2.

2.3 Specify scenario assumptions

We identified and described the main driving forces of global change, with different degrees of challenges to mitigation and adaptation, based on existing scenario frameworks. We explored future socioeconomic and climate driving forces framed by two reference global change scenario frameworks (Moss *et al.*, 2010), i.e., the SSPs (O'Neill *et al.*, 2017; Riahi *et al.*, 2017) and the RCPs (van Vuuren *et al.*, 2011), respectively. The SSPs chart future underlying socioeconomic development, including five pathways to 2100: SSP1 (sustainability), SSP2 (business-as-usual), SSP3 (regional rivalry), SSP4 (inequality), and SSP5 (fossil-fuelled development) (O'Neill *et al.*, 2017). The RCPs represent the climate forcing levels of different possible futures with long-term pathways to certain concentration levels of CO_2 by 2100 and beyond (Meinshausen *et al.*, 2020; van Vuuren *et al.*, 2011), including (originally) four emissions trajectories to 2100 (and beyond) with different levels of global radiative forcing from 2.6, to 4.5, to 6.0, to 8.5 W m^{-2} (van Vuuren *et al.*, 2011). The emissions trajectory of 1.9 W m^{-2} was added later as a pathway to 1.5 $^{\circ}$C to the end of the century (Rogelj *et al.*, 2019).

Although different forcing levels could be achieved under different socioeconomic scenarios, a specific RCP is often associated with each SSP (as also used in the sixth Climate Model Intercomparison Project (CMIP6)) considering consistency between their narratives and their plausibility (O'Neill *et al.*, 2016). We selected our benchmark SSP-RCP scenarios for implementation in the same way. We considered the plausibility of selected combinations as well as their application frequency across 715 studies (published between 2014 and 2019) that used integrated scenarios, based on a recent review by O'Neill *et al.* (2020). For example, we assumed that a high and a low radiative forcing of 8.5 and 2.6 W m^{-2} can most likely occur under the societal development of SSP5 and SSP1 which focus on highly polluting and sustainable futures (respectively). The radiative forcing of 8.5 and 2.6 W m^{-2} are also the most frequent levels applied in previous studies to these two SSPs. In the same way, we associated the radiative forcing levels of 4.5, 7.0, and 6.0 W m^{-2} to SSPs 2, 3, and 4 (respectively).

We excluded RCP 1.9 W m^{-2} from our analysis given the highly ambitious carbon dioxide removal (CDR) deployment assumptions in this scenario (Rogelj *et al.*, 2019) that is not explicitly represented in all integrated assessment models. Such high CDR deployment for achieving 1.9 W m^{-2} emissions trajectory also has an increased complexity of side effects on other sectors that are beyond the scope of this paper (see discussion in Section 4). In relation to each scenario combination, we also assumed climate mitigation policy assumptions, such as adoption of carbon capture and storage and carbon price, as indication of the efforts to reach the specified forcing levels (see description in Supplementary Table 1).

We elaborated how the future could unfold under each selected SSP-RCP combination in a set of coherent and internally consistent qualitative assumptions over the 21st century. The scenario assumptions represented the determinants of potential futures, both in socioeconomic (i.e., population, education, economy) and other sectoral domains (i.e., energy, climate, land, food and diet change). We adopted those scenario assumptions (related to socioeconomic conditions, energy, climate, land, and food and diet change) from the original SSPs (O'Neill *et al.*, 2017). We only selected those original assumptions that could be characterised in the FeliX model. For example, we did not include the SSPs' original assumption about 'technology transfer' given that technology collaborations between countries were not taken into account in our model. In another example, we used assumptions about 'improvement in investment in technology advancement' and the 'enhancement of energy technology efficiency' as two proxies consistent with our model's scope and structure to represent the SSPs' original assumption on 'energy technology change'.

We described the evolution of scenario assumptions qualitatively by 2100 under five SSP-RCP combinations (Supplementary Table 1). The qualitative descriptions were informed by the SSP storylines (O'Neill *et al.*, 2017) (which provided a descriptive account of different scenarios) and their sectoral extensions (which interpreted the storylines and provided a detailed account of energy (Bauer *et al.*, 2017), emissions (Meinshausen *et al.*, 2020), and land sectors (Popp *et al.*, 2017)). The internal consistency of our input assumptions across sectors (e.g., low population, high economic growth, high sustainability in SSP1) was similar to the SSP narratives. This internal consistency was important to relate the resulted scenario realisations to the exploration of a new model structure and its parametrisation rather than to having a totally differnet set of global change scenarios.

The qualitative scenario assumptions informed the implementation of scenarios in the next step by guiding in what range the model inputs should be and by providing a context to better understand and interpret model projections. Similar to the original idea of the SSPs, our scenario assumptions represented different degrees of challenges to mitigation (of the emissions from energy and land-use) and adaptation and their impacts on the society (O'Neill *et al.*, 2014; van Vuuren *et al.*, 2014). Four of the scenarios (i.e., SSP1-2.6, SSP3-7.0, SSP4-6.0, SSP5-8.5) indicated a combination of high and low challenges to adaptation and mitigation while the fifth scenario (SSP2-4.5) was representative of moderate mitigation and adaptation challenges.

2.4 Implement scenario assumptions in the model

We translated our scenario assumptions (Subsection 2.3) into influential model parameters (Subsection 2.2) for FeliX (i.e., calibration). Different model structures and simulation period do not allow for a harmonisation of scenario assumptions across various models, and several equally valid quantifications of the scenario assumptions can be implemented in models (as was the case for the five marker models of the SSPs (Riahi *et al.*, 2017)). The previously projected SSP scenarios (Riahi *et al.*, 2017) are also argued to be not exhaustive, and many plausible and important scenarios may be outside those standard ranges (Guivarch *et al.*, 2016; Rozenberg *et al.*, 2014), indicating the need for a more diverse translation of scenario assumptions. Accordingly, we implemented an internally consistent (across sectors) version of scenarios in the FeliX model, but with different values for model input parameters and uncertainty ranges that suited our model to enable the exploration of the implications of varying assumptions and hypotheses (see calibration details in Supplementary Methods).

2.5 Project scenario realisations with the model

We explored the uncertainty space of implemented scenario assumptions in the FeliX model and built a large number of model runs. Given the uncertainty in projection of model behaviour, we sampled deeply uncertain scenario assumptions that strongly influence the future (see the design of experiments details in Supplementary Methods). We simulated and evaluated scenarios against a diverse suite of socioeconomic and environmental outputs over time under a large ensemble of samples from the uncertainty space to understand the full scale of variation in scenario performance. Each sample from the uncertainty space is an internally consistent set of assumptions representing a possible scenario realisation, called a *state of the world (SOW)*.

In projecting scenarios, we assumed that there is an uncertainty inherent in the calibration of influential model parameters. We also assumed that there could be an uncertainty in the timing of change in the value of model parameters, i.e., from their BAU to calibrated values, to account for the delay in the emergence of scenario assumptions (e.g., diet change may not happen till 2025, and it may only gradually emerge from then). This delayed, gradual emergence of scenario assumptions through the model parameters was consistent with the implementations of the shared socioeconomic pathways in marker models (van Vuuren *et al.*, 2017). Using the parameter setting of each scenario (Subsection 2.4) and their uncertainty space, we simulated the global trajectories of socioeconomic, energy, climate, and land and food sectors from 2020 to 2100 with the FeliX model. We assessed whether our projections provide an internally consistent story across different sectors within each scenario, aligned with original SSP narratives (O'Neill *et al.*, 2017).

2.6 Compare the new projections with those of other models

In the last step, we analysed the resulting database of model runs (Subsection 2.5) and compared our projections across socioeconomic, energy, climate, and land and food sectors with the projections of marker integrated assessment models, including IMAGE (Bouwman *et al.*, 2006; van Vuuren *et al.*, 2017), MESSAGE-GLOBIOM (Fricko *et al.*, 2017; Riahi *et al.*, 2007), AIM (Fujimori *et al.*, 2017), GCAM (Calvin *et al.*, 2017), and REMIND-MAGPIE (Kriegler *et al.*, 2017), for the same SSP-RCP combinations. This comparison did not aim for agreement with other models, and was rather focused on differences and the new insights we arrived at that would not have been possible without modelling of scenarios with a non-marker model of different structural complexity.

3 Results and discussion

3.1 Scenario realisations

The quantification of scenarios across sectors with the FeliX model provided internally consistent outcomes across sectors (Figure 4). First, FeliX's projected SOWs under SSP1-2.6 represented an inclusive and environment-friendly future for sustainable development. The results showed a consistently high socioeconomic prosperity across education, population, and economy. Access to all levels of education (as a proportion of population size), especially higher education, increased (Figure 4d) with improvement in gender inequality. Global population peaked around mid-century and came under control (i.e., declined) significantly by 2100 due to a declining fertility rate (Figure 4a). Economic growth boomed due to fast technological progress (Figure 4e). The socioeconomic prosperity paved the way for sustainability transitions across different sectors. This involved major transformations in the energy sector.

While rapid economic growth would normally increase overall energy use, the input assumption of widespread energy-efficient technologies and a transition to low energy intensity services in SSP1-2.6 (Supplementary Table 1) attenuated the increase in energy demand (Figure 4h). The input assumptions of high investment and technological progress, high environmental consciousness, increasing production costs (e.g., carbon price costs) of using fossil energy, and the steep cost reduction of renewable technologies also made the model meet most of the energy demand through adoption of renewable (especially solar) energy (Figures 4l to 4n).

Similar sustainability transitions were observed in the food and land sector under SSP1-2.6. Environmental consciousness from high educational attainment (especially at tertiary levels) along with low population growth promoted healthy diets with low animal-calorie shares (Figure 4q). This also coincided with land productivity growth and high crop and livestock yield (because of input assumptions on improvement in land managerial practices) resulting in less need for the expansion of cropland and pasture (Figures 4r, 4s, and 4u) and a sharp decline in deforestation (Figure 4t). Transition to renewable energies, sustainable land-use change, and lower meat consumption, together with a strong climate policy regime (e.g., carbon price, carbon capture and storage for fossil fuels; see Supplementary Table 1) created a high potential for mitigation with low-range emissions (Figure 4w) and low radiative forcing levels (Figure 4v) by 2100.

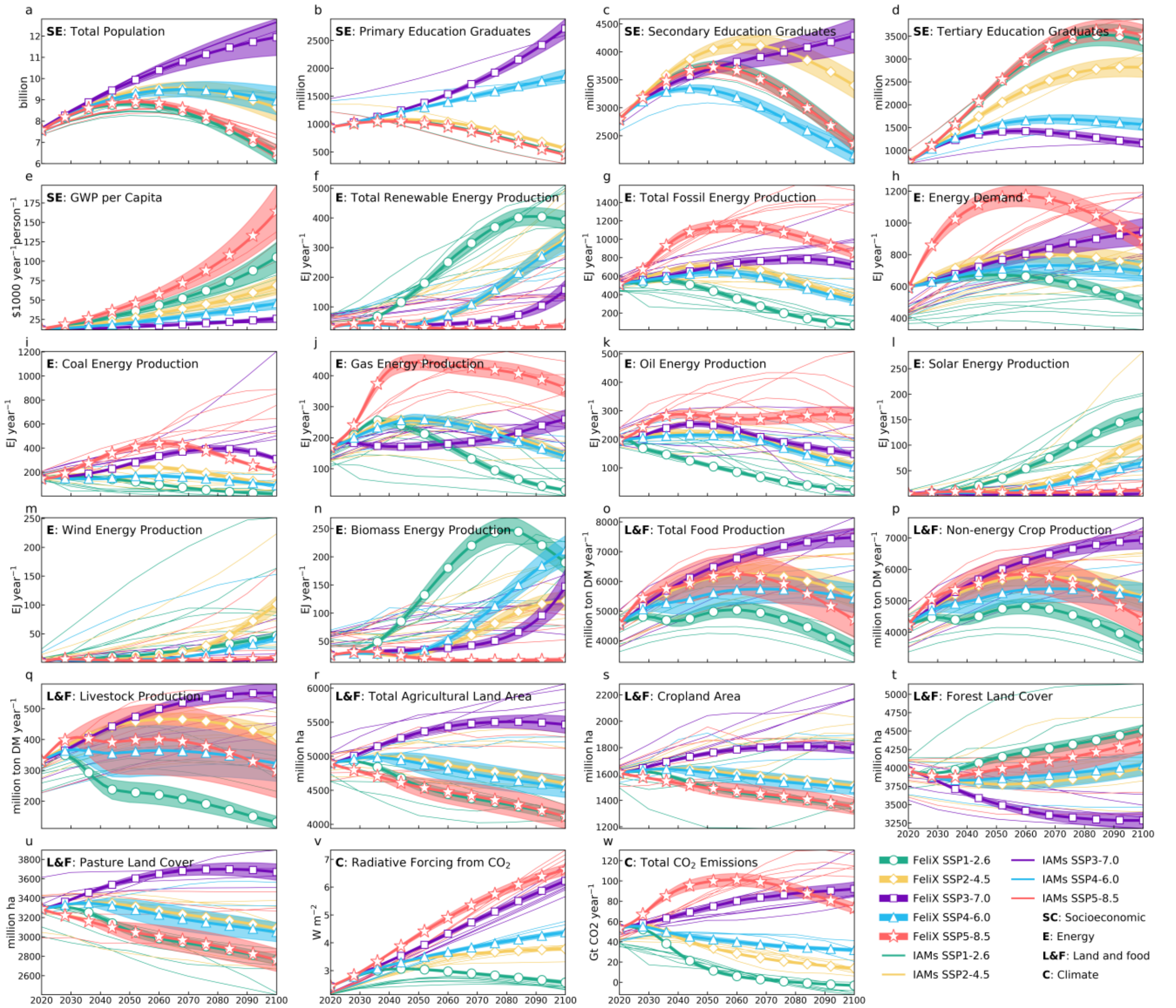

Figure 4. Scenario projections with the FeliX model (envelopes) and their comparison with other projections. This included the comparison with the projections of major demographic and economic models (Dellink *et al.*, 2017; Samir & Lutz, 2017) and integrated assessment models (Bauer *et al.*, 2017; Calvin *et al.*, 2017; Fujimori *et al.*, 2017; Kriegler *et al.*, 2017; Popp *et al.*, 2017; Riahi *et al.*, 2017; van Vuuren *et al.*, 2017) (thin lines). Projections cover the period 2020-2100 with an annual time step. See Supplementary Figure 2 for the detailed specification of projections with other IAMs.

The SSP2-4.5 projections followed the continuation of past and current (business-as-usual) trajectories across all sectors. The results showed a moderate growth in all socioeconomic sectors (population, education, economy) (Figures 4a to 4e), a higher energy demand, and a slower transition to renewable energy compared to SSP1-2.6 (Figures 4f to 4n). There was also a moderate rate of agricultural land expansion and deforestation and a relatively higher animal caloric supply (Figures 4o to 4u) due to input assumptions on the continuation of current (high meat) diet regimes. Together, these trajectories resulted in a higher level of emissions and radiative forcing compared to SSP1-2.6, but still lower than other scenarios due to moderate climate change mitigation policies (Figures 4v and 4w).

The SSP3-7.0 projections represented a high population, consumption, and environmental footprints scenario. The results showed the low-achieving socioeconomic projections among all scenarios (Figures 4a to 4e). A very slow economic growth led to an underdeveloped education system, especially at the tertiary level, which limited the training of a skilled labour force and created further challenges for economic development. Slow economic progress along with limited educational opportunities induced rapid population growth and declining wellbeing and life expectancy across the population. A relatively weak economy normally has a reduced demand for energy. However, input assumptions around low environmental standards and poorly performing public infrastructure in this scenario (Supplementary Table 1) increased energy demand compared to the business-as-usual trajectories (Figure 4h).

Transition to renewable (i.e., wind and solar) energy was slower in SSP3-7.0 compared to the business-as-usual (Figures 4l to 4n) due to input assumptions around low energy technology improvement (i.e., efficiency), limited investment in expanding installed renewable energy capacity, and lower production cost of fossil energy (i.e., no limit on emissions and carbon price for fossil fuels). In the land and food sector, low crop and livestock yield (due to poor land management practices) and increasing demand for animal calories from the increasing population necessitated the rapid expansion of cropland and pasture to address food insecurity (Figures 4o to 4u). A combination of booming population with declining trends of other socioeconomic systems, high fossil energy dependency, high meat consumption with rapid agricultural land expansion, and a lack of strong global climate change mitigation policies for the energy and land sectors resulted in high emissions and high radiative forcing levels (Figures 4v and 4w), posing significant challenges to mitigation in SSP3-7.0.

The SSP4-6.0 projections showed moderate trajectories in socioeconomic systems (i.e., population, education, economy) with trends better than business-as-usual and SSP3-7.0, but not at the same level of prosperity as in SSP1-2.6 and SSP5-8.5 (Figures 4a to 4e). Transition in the energy sector (from fossil to renewable sources) (Figures 4f to 4n) and food production and the expansion of agricultural lands (Figures 4o to 4u) also had relatively similar low and high trends (respectively) compared to business-as-usual. These socioeconomic, energy, and food and land trajectories together resulted in a moderate (compared to business-as-usual) emissions and radiative forcing (Figures 4v and 4w), leading to relatively low challenges to mitigation.

The SSP5-8.5 was a promising socioeconomic future at the cost of an unsustainable environmental outlook driven by a highly polluting and high-consumption lifestyle. The projections showed a similar level of socioeconomic prosperity to SSP1-2.6, with equally low population and high educational attainment, and even higher economic growth (Figures 4a to 4e). However, socioeconomic development in this scenario resulted in high, resource-intensive consumption, with severe impacts for energy and climate. Rapid economic growth promoted a lifestyle with the highest energy demand among all scenarios (Figure 4h). However, contrary to SSP1-2.6, this high energy demand was not offset by a transition to low energy intensity, efficient renewable energy technologies, nor an environmental consciousness around consumption impacts (Supplementary Table 1).

Despite rapid economic development and technological advances, the reliance on fossil fuels as a cheap source of energy remained much higher in SSP5-8.5 (compared to other scenarios) to meet the increasing energy demand (Figures 4i to 4k). In the food and land sector (Figures 4o to 4u), a lower population growth along with the effect of a relatively high crops and livestock yield (because of technological advances under SSP5) resulted in crop and livestock production and agricultural land area lower than the business-as-usual (but still higher than SSP1-2.6). This lower agricultural land area also resulted in a slightly improving trajectory for forest land indicator (Figure 4t). In FeliX's model structure, decrease in one land-use type is directly linked and contributes to increase in another land-use type (see model description in Supplementary Methods). The effects of all sectors together, mostly driven by a fossil-fuel-dependent energy system in the absence of universal climate polices, resulted in the highest emissions and radiative forcing in SSP5-8.5 among all scenarios, creating significant challenges to mitigation (Figures 4v and 4w).

3.2 Divergence from other projections

The modelling of our scenario assumptions resulted in internally consistent storylines similar to the SSPs (O'Neill *et al.*, 2017), but not necessarily with the same quantitative projections to those of other integrated assessment models (Riahi *et al.*, 2017), due to the new model structural complexity (Subsection 2.1) and different parametrisation (Subsection 2.4). While the scenario projection of marker IAMs (Figure 4) can be interpreted as being representative of a specific SSP-RCP development, they are not to be considered as central, median, or most-likely future developments. This means that for each SSP-RCP combination, numerous alternative projections are possible, and they are equally valid—as long as they are internally harmonious. The projection of scenarios with the FeliX model presented some of these equally valid, yet divergent futures to other model projections. Among the FeliX's divergences from the projections of other IAMs, three are more prominent.

First, the FeliX's projections of coal production in SSP5-8.5 were lower than projections from other marker IAMs from 2070 onwards (Figure 4i), showing more promising futures for renewable energies and a faster decline in fossil energies, even in the fossil-fuelled development pathway. This can be explained by the energy market share structure in FeliX where reduction in energy production from one source is compensated by energy from other (more price-competitive) sources. This model structure, along with assumptions about the declining cost of production from other energy sources over time, made coal less cost competitive compared to other fossil (i.e., gas, oil) as well as renewable (i.e., solar, wind) sources. This propagated a more rapid decline in coal production consistently across all scenarios (more noticeably in SSP5-8.5) in the FeliX model. The issue of conservative assumptions on renewable costs in the global climate (IPCC) scenarios (and hence less competition that can reduce fossil energy production) has been discussed in the literature (Eker, 2021; Jaxa-Rozen & Trutnevyte, 2021). A lower coal projection in FeliX is also more consistent with the recent governments' pledges for coal phase-out in the 2021 United Nations Climate Change Conference. Similar variations, resulting from differing model structural complexity and parameterisation, were observed among other integrated assessment models where some attributed greater priority to some energy technologies over others. For example, REMIND-MAGPIE and MESSAGE-GOLOBIOM had the highest solar and MESSAGE-GOLOBIOM had the lowest share of oil across all scenarios compared to other models. Despite this lower coal production compared to other models, coal production in SSP5-8.5 projected by FeliX still remained much higher than renewable energy production in the same scenario and was also higher than coal production in other FeliX's SSP-RCP projections. This maintained an internal consistency with the 'fossil-fuelled development' narrative (O'Neill *et al.*, 2017).

Second, FeliX's projections varied from those of other IAMs in food and land sector (most notably in SSP1-2.6 and SSP3-7.0), bringing new insights about the impacts of sustainable diet shift (from meat to vegetable) on food demand, food production, and land-use change. The observed variations in food and land are primarily linked to FeliX's diet change structure, an additional sub-model compared to other marker models. In FeliX, demand for agricultural land is driven by the size of food production, which itself is designed to meet food demand. This means that an increase or decrease in food consumption can directly impact food production and agricultural land expansion. The food demand and consumption of vegetables and meat in FeliX were modelled mainly through the diet change sub-model which formalised sustainable diet shift (i.e., reduction in meat consumption) in food systems based on behavioural factors (e.g., social norms and value driven actions) and educational attainments of the population per gender (Eker *et al.*, 2019). This linked to the food demand from various food categories (animal-based and plant-based foods), and subsequently to food (livestock) production, to demand for arable land (pasture and cropland), and to land-use change (i.e., deforestation). Diet (as a lifestyle driver) was mentioned in the original storylines of shared socioeconomic pathways (O'Neill *et al.*, 2017), but it was not explicitly modelled with its feedback interactions in most of the major integrated assessment models. However, modelling of diet change, as shifting social norms and changing patterns of human behaviour in food consumption, has become increasingly important (Willett *et al.*, 2019), with impacts on multiple SDGs (food, health, responsible consumption, biodiversity conservation) (Herrero *et al.*, 2021). Given assumptions on low caloric food consumption per person per year and low animal calories diet share in SSP1-2.6 (and the opposite in SSP3-7.0), the FeliX projections resulted in low livestock production (Figure 4q), low pastures and croplands (Figures 4s and 4u), and more forest land (Figure 4t) in SSP1-2.6 (and vice versa in SSP3-7.0).

Third, the combination of a sharper decline in coal production as well as varied food consumption patterns in FeliX (as explained above) resulted in lower projections of CO_2 emissions, most notably in SSP5-8.5, compared to the other models. This brings a new insight that the consideration of diet change impacts and more aggressive assumptions on fossil fuel reduction can make CO_2 emissions less likely follow the projection of current high-emission scenarios (i.e., SSP5-8.5). Such lower emission projections are aligned with the tracked emission developments over the past three decades which followed the middle of projected emission scenarios (Pedersen *et al.*, 2020). It also echoes the recent critiques about the relevance of high-emission RCPs (Hausfather & Peters, 2020), signifying the importance of considering a broader range of emission projections in sustainability analysis.

3.3 Scenario implications for sustainable development

The complex and deeply uncertain multisector dynamics that underlie the SDGs resulted in substantially varied outcomes for sustainable development across different scenarios and indicators (Figure 5). Among the generated SOWs, the accumulation of changes in SSP1-2.6 between 2050 and 2100 created a promising long-term trajectory for sustainable development. However, this was not the case in generated SOWs under other scenarios, driven by counteracting interactions between future socioeconomic and environmental drivers. The trends in some of the major indicators are described here for illustration while the detailed projections of all indicators are available in Figure 5 and the online dataset.

Among the socioeconomic indicators for sustainable development, Gross World Product (GWP) per capita (Figure 5e-i), adolescent fertility rate (Figure 5b-ii), and mean years of schooling (Figure 5c-i) were the three with the fastest improvement over the century in SSP5-8.5 and SSP1-2.6 (across SOWs) by 2030 and beyond. This was due to input assumptions on investment in high-quality and well-functioning education (Figure 4d) and declining population growth (Figure 4a) under these two scenarios. Despite similar performance in socioeconomic indicators, the human prosperity and economic growth created two different pathways for environmental impacts and for achieving sustainable development under SSP1-2.6 and SSP5-8.5.

In SSP1-2.6, the high level of socioeconomic prosperity led to improving trajectories in major energy and climate indicators by 2030. In a longer timeframe and by 2100, the increasing scale of positive socioeconomic change in this scenario achieved more than 85% (global average) share of renewable energy supply (Figure 5d-i), close to 430 ppm CO_2 concentration (Figure 5g-i), and < 2 degree °C global temperature change (Figure 5g-ii). The SSP1-2.6 scenario also resulted in a significant drop in total agricultural activities (Figures 4r), positively impacting several SDG indicators related to food and land-use change. Among these positive impacts was SSP1-2.6's declining trend in (land-based) animal calorie supply (Figure 5a-ii) due to a decreasing population after 2050 (Figure 4a) and lower meat consumption. Reducing demand for food through responsible consumption and collective global action on food choices under this scenario could alleviate the pressure from the COVID-19 pandemic on the food system, helping those worst-affected by the distributional impacts on food supply chains. The SSP1-2.6 scenario also outperformed other scenarios in some of the major responsible production and biodiversity conservation indicators, such as yield improvement (Figure

5a-i), reduced pressure from agricultural land expansion and fertiliser use (Figures 5f-i, 5f-ii), and less deforestation and biodiversity loss (Figures 5h-i, 5h-ii).

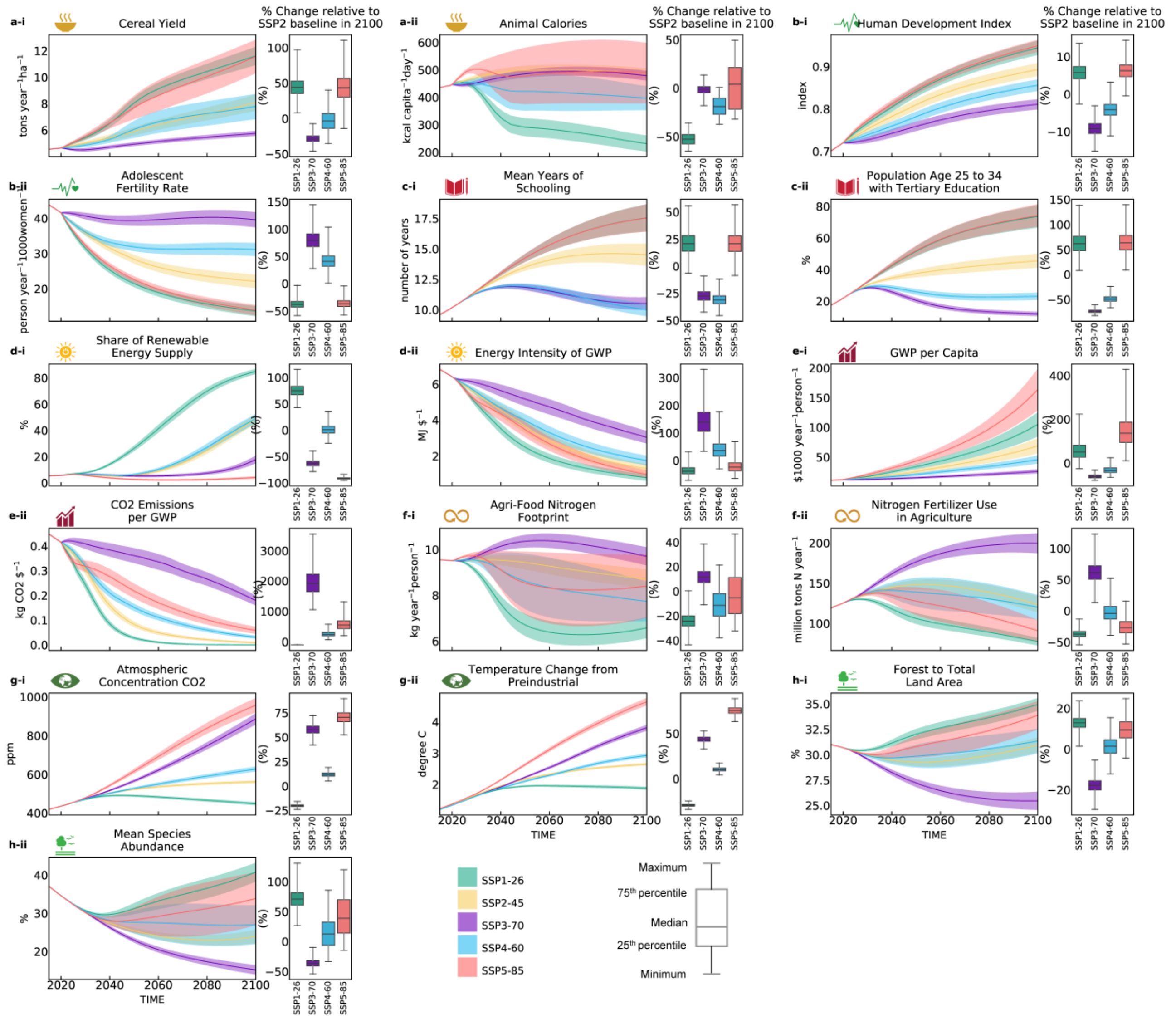

Figure 5. The implications of modelled scenarios for sustainable development across 50,000 SOWs and in 16 indicators. In each subplot, the envelope plots show each indicator's trajectory across five scenarios with descriptive statistics (mean and standard deviation) to represent the average projected value and the uncertainty range of each indicator's projection. The box plots show the comparative of performance of each scenario compared to the business-as-usual's trajectories (i.e., baseline SSP2-4.5). This shows what would happen (i.e., the scale of improvement or deterioration in each indicator) if we deviate (positively or negatively) from current trajectories (i.e., business-as-usual).

By contrast, socioeconomic prosperity in SSP5-8.5 resulted in the fastest growth in the share of fossil fuels in energy supply (Figure 5d-i) driven by increasing demand from high energy intensity of industry and services (Figure 4h). Reliance on fossil fuels in this scenario translated into severe climate impacts from (energy-related) high CO_2 concentration (Figure 5g-i) with global temperature continuing to rise to almost 4.5 degree °C by 2100 in all simulated SOWs (Figure 5g-ii). This imposed a severe risk for achieving the IPCC climate targets (Rogelj *et al.*, 2019). The SSP5-8.5 scenario also resulted in a high land-based animal calorie supply up to 50% (across all SOWs) higher than the business-as-usual trajectories driven by the economic welfare combined with high meat-based diets

(Figure 5a-ii). This led to the higher production of crops in this scenario as livestock feed (Figure 4q). However, high crop and livestock yields and effective land management practices fuelled by high GWP and rapid technology advances, as described in this scenario's assumptions (Supplementary Table 1), enabled the achievement of high food demand and production with less agricultural land (Figure 4r). This resulted in improving trajectories in indicators related to forest land (Figure 5h-i) throughout the 21st century.

Far less improvement occurred in SSP3-7.0 and SSP4-6.0 across all indicators and SOWs. The global trajectories under these two scenarios deteriorated in most of socioeconomic, energy, climate, and biodiversity indicators. This resulted from the combined effects of the medium to high population (Figure 4a), slow economic growth (Figure 4e), low investment in higher education (Figure 4d), high energy demand from inefficient and high energy intensity infrastructure (Figure 4h), low diffusion of renewable energy (Figure 4f), and extreme pressure on lands from agricultural activities and high animal calorie consumption (Figures 4r and 4q), as discussed in Subsections 3.1 and 3.2. For instance, trends over the century reached around 3-4 degree °C warming (compared to the pre-industrial level), significantly exceeding the 1.5-2 degree °C target from the Paris Agreement (Figure 5g-ii). Similar negative drivers across these two scenarios also resulted in extreme-range trajectories in indicators related to food production (Figure 5a-ii), fertiliser use (Figure 5f-i, 5f-ii), and biodiversity across all SOWs by 2030 and beyond (Figure 5h-i, 5h-ii). For example, high rates of fertiliser application in agriculture (up to 40% higher than business-as-usual; Figure 5f-i) and the steep decline in forest land and species abundance (up to 30% and 50% decline compared to business-as-usual respectively; Figure 5h-I, 5h-ii) under SSP3-7.0 were attributed in the model to the complex underlying dynamics of high population growth along with unhealthy diets with a high animal calorie diet that increases the demand for feed crops. As a result of this high feed demand, the pressure on natural and agricultural lands increased strongly (Figure 4r), resulting in further demand for fertiliser application and greater deforestation and biodiversity loss.

4 Conclusions and future work

Interacting systems, with multisectoral dynamics that occur at an unprecedented pace, can create complexity and uncertainty in understanding the impacts of future socioeconomic and environmental change on sustainable development. Despite the popularity of standard (marker) integrated assessment models as widely used tools to understand environmental and societal risks of climate change, the knowledge that is put into these models (e.g., conceptual framing, boundary conditions, model structure, parametrisation) is imperfect, limited, and uncertain (Walker *et al.*, 2013). This uncertainty challenges the ideal of the marker models as the projection tools, which turn best available knowledge into best estimates. One way of dealing with this combination of uncertainty and complexity is through scenario exploration with a greater diversity of models that have new modelling paradigms (e.g., system dynamics), different structural complexity (e.g., feedback-rich), and alternative assumptions, and can better simulate the underlying multisectoral dynamics for the assessment of sustainable development (Moallemi *et al.*, 2020a).

We implemented global scenarios in a non-marker, SDG-focused integrated assessment model to investigate the new uncertainty of future projections for sustainable development. First, it contributed to sustainability science by exploring broader implications of global scenarios beyond the original foci of climate change and in sustainable development across multiple SDGs. Second, the methodology used for the adoption of global scenarios was a generalisable contribution too. The methodology can be adopted beyond the SDGs and in the projections and quantifications of other sustainability frameworks (e.g., social and planetary boundaries (Leach *et al.*, 2013; Steffen *et al.*, 2015), safe and just operating space (Raworth, 2012), doughnut economics (Raworth, 2017)) to bring new insights about social and biophysical indicators that are not directly measured in the SDGs. The use of this methodology also allows a greater diversity of similar non-marker models to be adopted for global change and sustainability assessments; something important for expanding the current limits of benchmark scenarios and exploring a larger uncertainty space driven by new model structures (e.g., diet change impacts).

While we evaluated the trajectories of a subset of SDG indicators to demonstrate the implications of global scenarios, measuring the actual progress in all SDGs or discovering the individual contribution of socioeconomic (SSP) versus climatic (RCP) drivers in making the progress was not our focus. An important next step is to focus on SDG progress analysis specifically and model a larger diversity of indicators under all SDGs (Allen *et al.*, 2019; Soergel *et al.*, 2021). One can also adopt post-processing techniques (e.g., scenario discovery cluster analysis (Guivarch *et al.*, 2016; Rozenberg *et al.*, 2014)) to identify the main socioeconomic and climate driving forces of each SDG indicator and to quantify the extent of their (positive or negative) contributions to the SDG progress.

While we explored the prevalent uncertainty of several indicated model parameters, we acknowledge that we did not include all forms of uncertainties, and not specifically those severe forms of uncertainty (i.e., unknown unknown circumstances or state of total ignorance), which cannot be fully represented in models (Stirling, 2010). Future work is needed to incorporate other techniques and approaches (e.g., scenario discovery, robustness analysis, adaptive policy-making) to identify tipping points as warning signs, employ monitoring processes, and execute multiple pathways to be prepared for future contingencies. These can enable proactive and anticipatory responses to external shocks and help decision-makers in keeping human and environmental systems on-track towards sustainability targets in the face of severe uncertainties. A longer-term analysis of climatic and biophysical uncertainties (e.g., the carbon cycle change, atmospheric composition, nitrogen cycle) in a time horizon beyond 2100 (Meinshausen *et al.*, 2020) may also reveal new insights about (de)stabilisation and multi-century dynamics of sustainability indicators, which cannot be properly understood in a century-long timeframe.

Further enhancing the robustness of insights obtained about the SDGs requires the expansion of scenario space and its uncertainty exploration to include similar sustainability analyses over many other possible combinations of SSPs and RCPs (O'Neill *et al.*, 2020). However, this comes at the expense of increasing the computational costs of simulations. Our model-based assessment of the SDGs was no exception. Our results and their interpretations in this article were based on the assumptions of only five specific SSP-RCP combinations, and there were other potential combinations that we did not investigate. For example, our most sustainable scenario was developed based on SSP1-2.6. While SSP1-2.6 can substantially control environmental damages from energy and climate impacts relative to our other scenarios, the SSP1-2.6 scenario is not still aligned with IPCC mitigation pathways which limit global warming to 1.5 degree °C (Rogelj *et al.*, 2018b). Future research can construct SSP1 in the FeliX model in line with the pathways of more aggressive actions (i.e., more ambitious Nationally Determined Contributions under the Paris Agreement) and more extreme mitigation pathways (e.g., aligned with 1.9 W m^{-2} radiative forcing level or with pathways proposed by the IPCC 1.5 (IPCC, 2018)). This could potentially improve the performance of the SSP1 scenario across energy and climate indicators (e.g., faster emissions reduction) compared to our results, driven by for example a greater reliance on atmospheric CO_2 removal technologies and practices (Smith *et al.*, 2016). However, it should be noted that more aggressive assumptions such as a very high level of CO_2 removal have not been demonstrated in practice and may cause other sustainability issues such as competition with food and agricultural sectors for land and water (Rogelj *et al.*, 2018b). Hence, policy cost and feasibility assessment become an important research direction in future studies with scenarios of more aggressive emissions reduction and with potential spillover effects on other sectors (Brutschin *et al.*, 2021).

The further enhancement of the robustness of results also requires the expansion of feedback interactions included in models. Sustainable development is driven by dynamic interactions between human and natural systems (van Vuuren *et al.*, 2012). For example, climate change (in the natural system) can increase heating and cooling energy demand (in the human system), and at the same time the resulted impacts on energy demand can interact with and deteriorate climate and air pollution. While FeliX integrated some of these destabilising (reinforcing) and stabilising (balancing) feedback interactions as an indivisible whole in a system dynamics model, it still did not model several of these interactions underlying different SDGs (e.g., the tipping point effects of climate change on wildfires, deforestation). Research is needed to further integrate the representation of socioeconomic factors in climate and carbon cycle dynamics and the inclusion of biogeophysical processes in energy production, land-use change, and emissions. Examples can include interactions between climate change and crop growth (e.g., carbon concentration reduces natural vegetation), land-use (e.g., prolonged precipitation influences land management decisions), energy use (e.g., rising temperature increases energy demand), and human behaviour (perceived climate extreme event risks alter human emissions) (see Calvin and Bond-Lamberty (2018) for a recent review). A further modelling of feedback interactions can enable a better identification of effective interventions to maximise synergies and minimise trade-offs across sectors.

The discussion of scale and interactions between global, national, and local efforts in modelling the SDGs under uncertainty can also play a crucial role in future scenario modelling for the SDGs (Verburg *et al.*, 2016). In this article, we characterised the future development of socioeconomic, food and land, energy, and climate systems at a global scale. Other studies have also mostly analysed these scenarios either at global (Randers *et al.*, 2019), regional (Soergel *et al.*, 2021), or national (Gao & Bryan, 2017) scales. However, large scale and global scenarios in reality translate into *local* changes in human interactions with the environment (Moallemi *et al.*, 2020b). Grassroots solutions led by local communities, cities, and businesses can also make synergies with the aspirations of the higher scales and significantly impact the unfolding of higher-level sustainability scenarios (Bandari *et al.*, 2021; Bennett *et al.*, 2021; Szetey *et al.*, 2021a, 2021b). This brings new challenges for modelling the cross-scale dynamics of scenarios that can account for both higher spatial and temporal resolutions where policy-making (e.g., carbon pricing) and biophysical processes (e.g., greenhouse gas emissions) operate, as well as for locally-specific and place-based dynamics, such as the representation of heterogeneous actors (Ilkka *et al.*, 2021) and their inequalities (Emmerling & Tavoni, 2021). Future work on integrated assessment modelling, therefore, requires capturing and better incorporating the societal dynamics of lower scales (beyond the currently global, regional, or national assumptions) in scenario exploration and projections for sustainability (Liu *et al.*, 2013). This can lead to more reliable insights for sustainable development that can account for the diversity of local preferences and priorities and the heterogeneities in the availability of resources across regions. Such insights enable a more just and inclusive sustainable development by tailoring the plans to the unique socio-ecological characteristics of each context (Moallemi *et al.*, 2019).

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Visualisation: E. A. Moallemi
Writing – original draft: E. A. Moallemi
Writing – review & editing: E. A. Moallemi, S. Eker, L. Gao, B. A. Bryan

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Conflicts of Interest

Authors declare no conflict of interest.

Code and Data Availability

The datasets/code generated during this study are available from https://zenodo.org/record/5339013. Further information and requests for resources and reagents should be directed to and will be fulfilled by Enayat A. Moallemi (email: e.moallemi@deakin.edu.au).

Supplementary Information

- Supplementary Methods
- Supplementary Figure 1. The convergence of parameter ranking and sensitivity index in the projection of model's control variables in year 2100, for the increasing number of sample size.
- Supplementary Figure 2. Scenario projections with the FeliX model and their comparison with the projections of major demographic and economic models.
- Supplementary Table 1. Qualitative assumptions of scenarios.
- Supplementary Table 2. The list of candidate uncertain model parameters used for sensitivity analysis.
- Supplementary Table 3. Key scenario parameters and their quantification in the FeliX model.

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Supporting Materials for

Diversifying models for analysing global change scenarios and sustainability pathways

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This PDF file includes:

Supplementary Methods

Model description

- *Population*, as the core sub-model, captures the dynamics of male and female population growth and ageing, and is directly linked to all SDGs through other sub-models that compute energy demand, food consumption, and water use, amongst others.
- *Education* computes the size of male and female population with primary, secondary, and tertiary education through feedback loops between enrolment and graduation rate, directly interacting with: SDG2 via the impact of education level on diet change and reduced meat consumption; SDG3 and SDG4 via improving wellbeing and educational attainment with higher number of graduates at all levels, and; SDG8 via providing the labour force necessary to power the economy.
- *Economy* computes economic outputs through a Cobb-Douglas production function where economic output is computed based on labour input, capital input from energy and non-energy sectors, new technology productivity factor, and ecosystems and climate change impacts. Economy interacts with all SDGs except for SDG4 (as educational attainment is not modelled in FeliX as a function of economic outputs).
- *Energy* computes (a total end-use) energy demand as a function of GDP per capita and population, the energy consumption and market share of three fossil (i.e., coal, oil, gas) and three renewable (i.e., solar, wind, biomass) sources, and the production of different (six) energy sources based on a detailed modelling of installed capability and their ageing process, energy technology advancement (e.g., learning curves), investments, and availability of resources (e.g., average sun radiation, exploration and discovery of new fossil resources). Energy interacts with most of the SDGs such as SDG7 through renewable energy production, SDG13 through reducing emissions from fossil fuels, and SDG15 by decreasing the demand for land-use change for deforestation for biomass generation.
- *Water* simulates water supply and demand across agriculture, industrial, and domestic sectors as a function of available water resources, drought out rate, the impact of climate change, water withdrawal, and the recovery of used water. Water interacts mostly with SDG2 through supplying water for agricultural activities and SDG3 by providing quality water for domestic use.
- *Land, Food, Fertiliser, Diet Change*, and *Biodiversity* are extensively described in the FeliX model documentation (Eker *et al.*, 2019; Walsh *et al.*, 2017). They simulate the change of four different land-uses, the demand and production of food (i.e., crop-based meat, pasture-based meat, dairy and eggs, plant-based products), feed, and energy crops, diet shift reflecting the proportion and type of meat consumption in the human food (five diet compositions), (nitrogen and prosperous) fertiliser uses and their footprints, and the restoration and extinction of species. The food consumption is primarily determined through the impacts of diet change (towards less meat diets) across different population segments (e.g., male and female, level of education), modelled based on two feedback mechanisms from psychological theories: diet change due to social norms and diet change due to a threat and coping appraisal (e.g., in response to climate change) (Eker *et al.*, 2019). The demand for agricultural land is balanced by increasing crop yields with fertilisation. The impacts of these sub-models are diverse across most of the SDGs. For example, the limitation of agricultural activities through diet change in SDG2 can substantially reduce pressure on deforestation in SDG15, and the impact of biodiversity conservation can subsequently impact general public health in SDG3.
- *Carbon Cycle* and *Climate* compute CO_2 emissions from the land and energy sectors, as well as the atmospheric radiative forcing and temperature change of the emitted CO_2 and their cycle and absorption through terrestrial reservoirs and oceans based on the C-ROADS model (Sterman *et al.*, 2012). They also model the effect of improvement in carbon capture and storage on controlling emissions. The radiative forcing of other gases (CH_4, N_2O, HFC) are read externally in the model via links to the RCP scenario database (van Vuuren *et al.*, 2011). See Walsh et al.(Walsh *et al.*, 2017) for the detailed equations of carbon cycle and climate modelling. These sub-models interact with most of the SDGs, and primarily with SDG13 through climate change impacts. FeliX models the effects of feedback interactions between climate change (i.e., increasing temperature or carbon concentration) and several other sectors, including biodiversity loss (e.g., species extinction rate), agricultural (crop and livestock) yield, life expectancy, economic growth, and water supply availability. However, the model still does not include some of other related biogeophysical feedbacks (e.g., the effects of wildfires on land-use change) (Calvin & Bond-Lamberty, 2018).

Model sensitivity analysis

With Morris elementary effects, we computed the sensitivity index, μ^*, from a total evaluation of $r \times (p + 1)$ experiments, where r is the number of sampling trajectories over the number of parameters $p + 1$ points. The μ^*, which shows the overall effect of a parameter on an output, can be sufficient on its own in providing reliable ranking of model parameters (Campolongo *et al.*, 2007). We generated experiments by systematically sampling random values (Morris sampling) using the Exploratory Modelling Workbench (Kwakkel, 2017) across 114 model parameters and computed μ^* using the SALib Library (Herman & Usher, 2017) implementation of this technique, both in the Python environment. To ensure that the ranking obtained from the μ^* elementary effects converges, we computed the sensitivity index of different samples of increasing size from 250 to 5,000 samples (equivalent to 28,750 - 575,000 experiments) and used the μ^* of the sample size of 2,000 (230,000 experiments), where the parameter ranking was stabilised (Supplementary Figure 1), as the reference. We also computed μ^* over time (i.e., 2030, 2050, 2100) to understand how the sensitivity of parameters can change in response to non-linear model behaviour throughout time (Figure 3).

While this can help in ranking model parameters, it does not still specify how many of the ranked parameters should be included in the modelling of scenarios. We systematically explored the impact of inclusion or exclusion across top-ranked parameters. This was a more reliable approach compared to setting *a priori*, subjective cut-off value for μ^* where a high cut-off value can lead to the inclusion of many parameters (some of which with negligible effects) and a low cut-off value can cause the exclusion of some important parameters that could potentially have significant effects, both of which with biased impacts on the identification of key model parameters.

To select influential parameters from the ranking results, we assumed that the *n* top-ranked parameters, where *n* can vary from 1 to all parameters, are those that are the most influential. We then systematically tested for what number of *n*, the metrics of sampling across the *n* top-ranked parameters have high correlations with the metrics of sampling across all parameters (i.e. maximum range of behaviour) (Hadjimichael, 2020). We tested the degree of correlation between the Latin Hypercube sampling across all parameters (Set 1), across the *n* top-ranked parameters (Set 2), and across all parameters except the *n* top-ranked parameters (Set 3). Ideally, if the *n* top-ranked parameters are the most influential, they should have the same impacts on outputs as when we sampled across all parameters (i.e., Set 1-Set 2 and Set 1-Set 3 correlations converge to 1 and 0 respectively). We started from $n = 1$ and increased $n = n + 1$ until sampling across the *n* top-ranked parameters (Set 2) generated at least 99% correlation with sampling across all parameters (Set 1). The generation and evaluation of the three sets for different number of n values resulted in 2,400,000 computational experiments. This approach in identifying influential parameters is more reliable compared to *a priori* cut-off value in the ranking results where the inclusion or exclusion of parameters can be biased to our subjective thresholds. *A priori* cut-off value in selecting the number of influential parameters can lead to either the inclusion of a large set of parameters (some of which with negligible effects) or the exclusion of some important parameters that could potentially have significant effects, both of which will make the identification of key parameters biased (Hadjimichael, 2020).

Model calibration

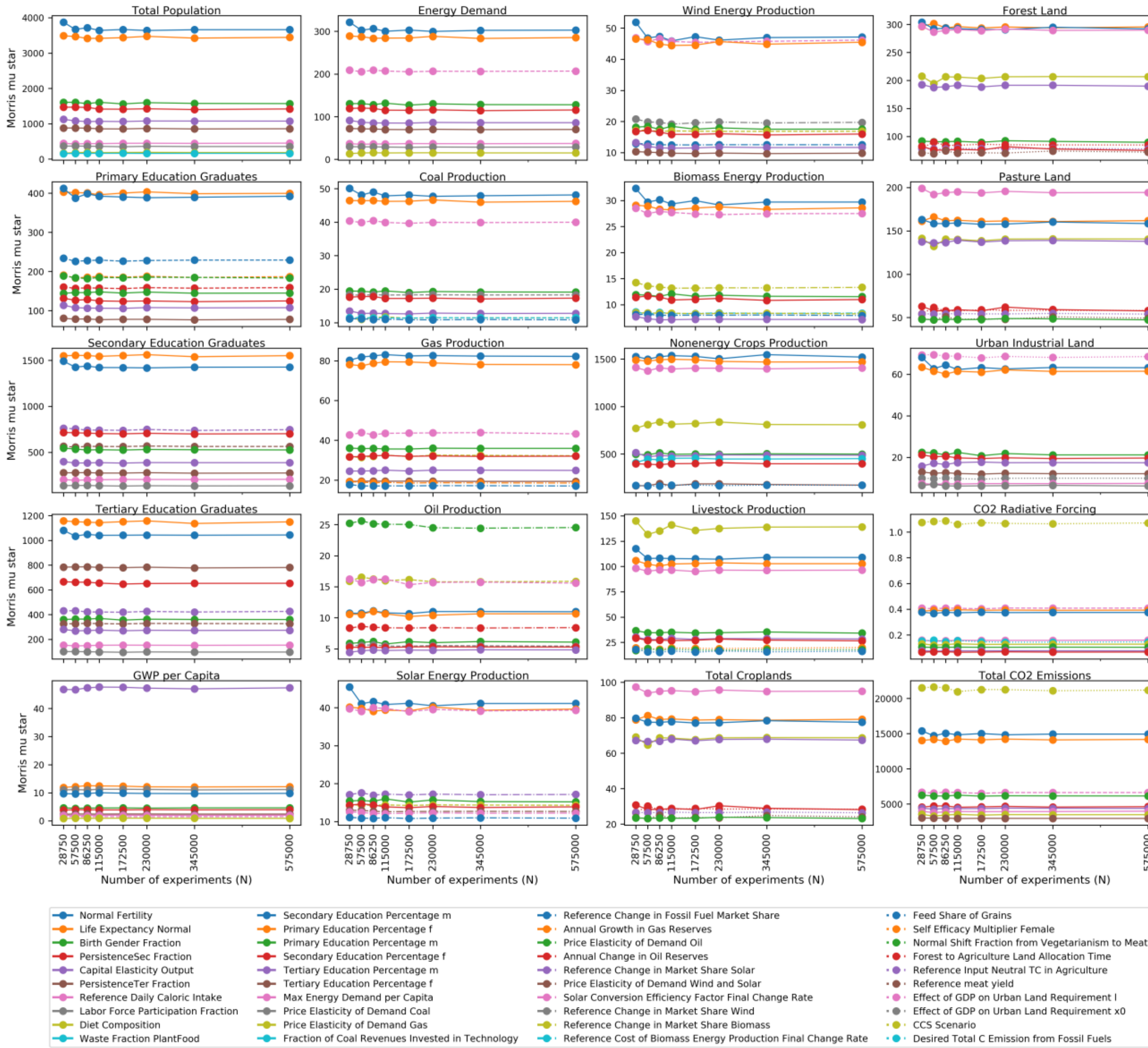
Among various influential parameters, those related to the demographic and macro-economic input assumptions were the only ones harmonised with other integrated assessment models as they form the fundamental underlying logic for each SSP, and their harmonisation is important for generating internally consistent scenarios. The original quantifications of these socioeconomic assumptions are also based on country-level, multi-dimensional (e.g., age, gender, level of education) mathematical modelling of demography and economy growth (Dellink *et al.*, 2017; Samir & Lutz, 2017), and therefore their estimates were considered as reference for FeliX (as well as across all other marker integrated assessment models). We used Vensim's built-in optimisation algorithm (i.e., Powell) to find the value of FeliX's (socioeconomic) parameters (Section 2.2) aligned with the reference demographic and economic model (Dellink *et al.*, 2017; Samir & Lutz, 2017). The objective function (also called payoff function) was defined as the weighted difference between FeliX's socioeconomic output variables and the quantification of the same outputs by formal demographic and economic models at each time step under each SSP-RCP scenario. The optimisation search under each scenario involved 1000 iterations from 5 different starting point (i.e., 5000 evaluation per scenarios) for different initialisation to avoid local minimum.

The quantification of non-socioeconomic parameters (related to energy demand, food consumption, etc.) was not harmonised with other integrated assessment models to allow the generation of other plausible futures. Their quantification was based on FeliX's initial parameterisation (previously calibrated by Eker *et al.* (2019), Walsh *et al.* (2017), and Rydzak *et al.* (2013)) and its variation across scenarios aligned with the scenario assumptions (Section 2.3). To illustrate, the influential FeliX's parameter related the diet composition was calibrated based on five groups of diet (Eker *et al.*, 2019). Diet composition 1 (sustainable) was when meat-eaters become flexitarian (limited animal-based foods) and vegetarians eat vegan (high plant-based foods). Diet composition 2 (relatively sustainable) was when meat-eaters adopt a healthy diet (moderate animal-based foods and high plant-based foods) and vegetarians eat reference vegetarian diet. Diet composition 3 (relatively sustainable) was when meat-eaters eat healthy diet and vegetarians eat a vegan diet. Diet composition 4 (slightly better than status quo) was when everyone (meat-eaters and vegetarians) is flexitarian (a mix of animal-based and plant-based foods), and therefore there is only a slight improvement from the current situation, but still on the same trends. Diet composition 5 (status quo) was when everyone follows the current reference meat and vegetarian diets (high meat and moderate vegetable consumption). Each of these diet compositions was assigned to a scenario consistent with our qualitative assumptions (Section 2.3) about environmental impacts of food consumptions. Other influential parameters were calibrated in the same way. Supplementary Table 3 includes the detailed quantified assumptions for uncertain model parameters under each scenario as well as information on the unit of each parameter.

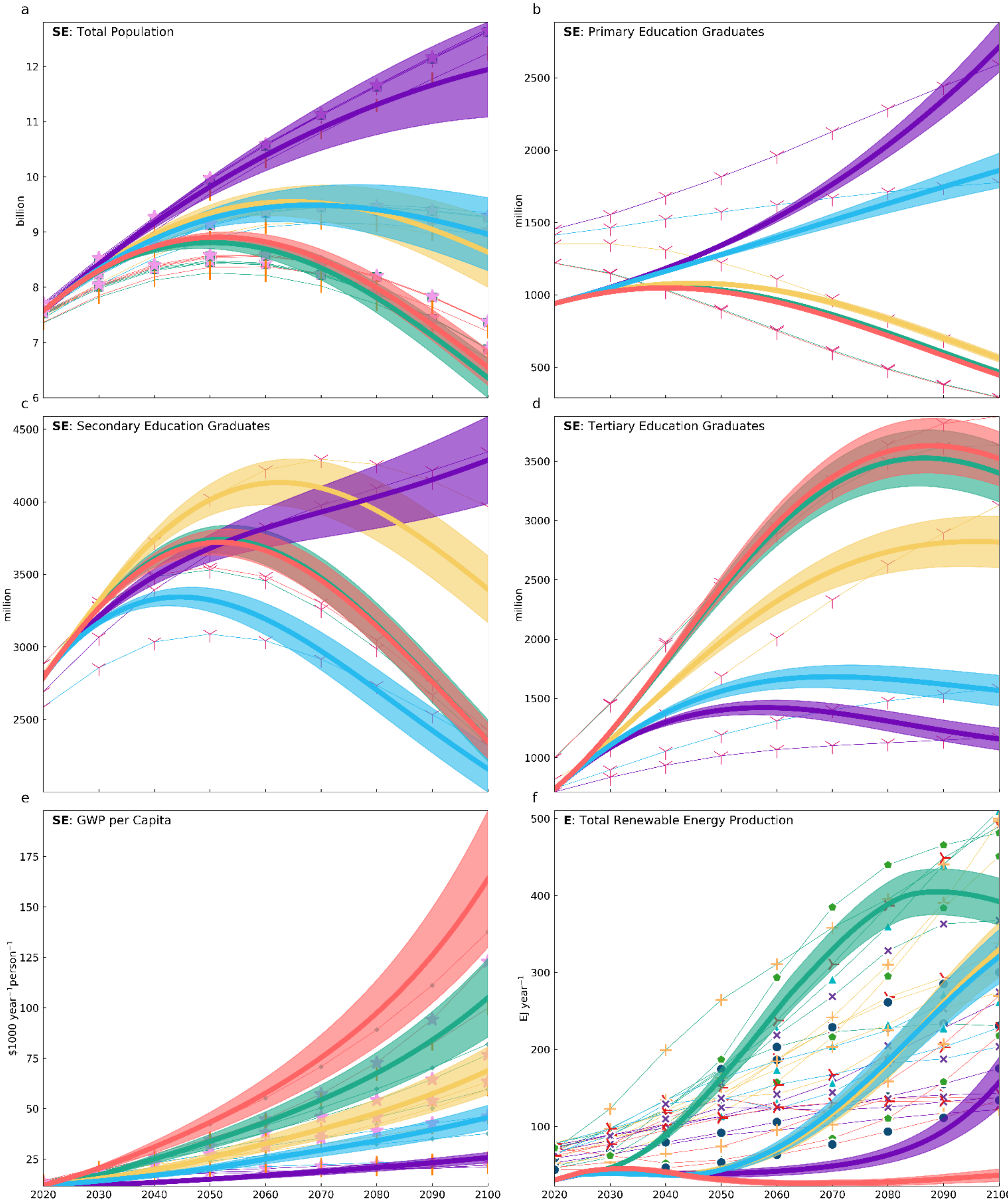
Design of experiments

We considered three aspects in designing the computational experiments. The first two aspects were *sampling method* and *sample size*, that together specified how to randomly collect assumptions from the uncertainty space of scenarios (e.g., population growth, GDP, technology advancement) to create an ensemble of SOWs. Complex, highly dynamic models such as FeliX can create non-linear and unpredictable model behaviour, and sampling uniformly may not be able to explore a sufficient range of model behaviour. We used Latin Hypercube Sampling (McKay *et al.*, 2000) to generate SOWs with the highest possible coverage of the uncertainty space and level of randomness, generating 50,000 SOWs across five scenarios (10,000 SOWs per each). We chose Latin Hypercube Sampling as it creates evenly spaced and distributed grid boxes in the uncertainty space and (quasi) randomly selects a sample from each grid box. This results in a sampling strategy that is more evenly distributed across the space compared to, e.g., uniform random sampling (Saltelli *et al.*, 2000). Latin Hypercube Sampling has been also suggested as suitable technique for the design of experiments in previous exploratory modelling studies (Bryant & Lempert, 2010). Sample size (i.e., the number of experiments to run) was selected based on the stability of performance indicators with increasing number of experiments.

The third aspect in the design of experiments was the delineation of the uncertainty range to sample from. Previous studies suggested alternative ways to delineate a multi-dimensional uncertainty space based on learning and feedback from the influence of uncertainties on model behaviour (Islam & Pruyt, 2016; Moallemi *et al.*, 2018). We specified the uncertainty range of 10-30% around the calibrated value of parameters, with the range's length varying between parameters depending on the meaningfulness of range's bounds for the model parameter and the interpretability of model response. For example, a highly sensitive parameter such as fertility rate, whose variation could impact various parts of the model, had a narrow uncertainty range for having reasonable projection of population size. Supplementary Table 3 includes the quantified uncertainty range of key scenario parameters under five selected scenarios (SSP1-2.6 to SSP5-8.5).

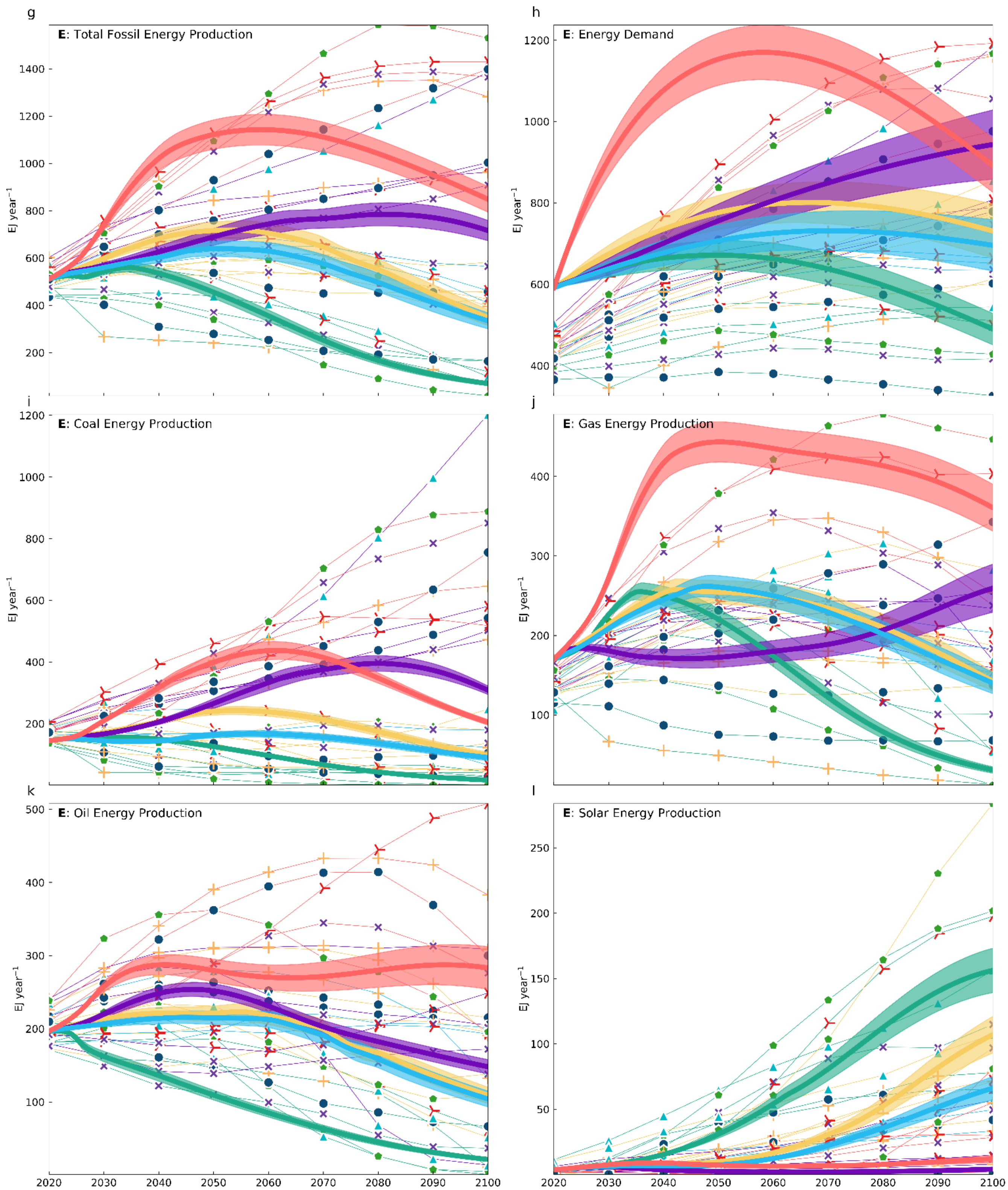


Supplementary Figure 1. The convergence of parameter ranking and sensitivity index in the projection of model's control variables in year 2100, for the increasing number of sample size. The figure only shows the convergence of top 10 most sensitive parameters which for better visibility.

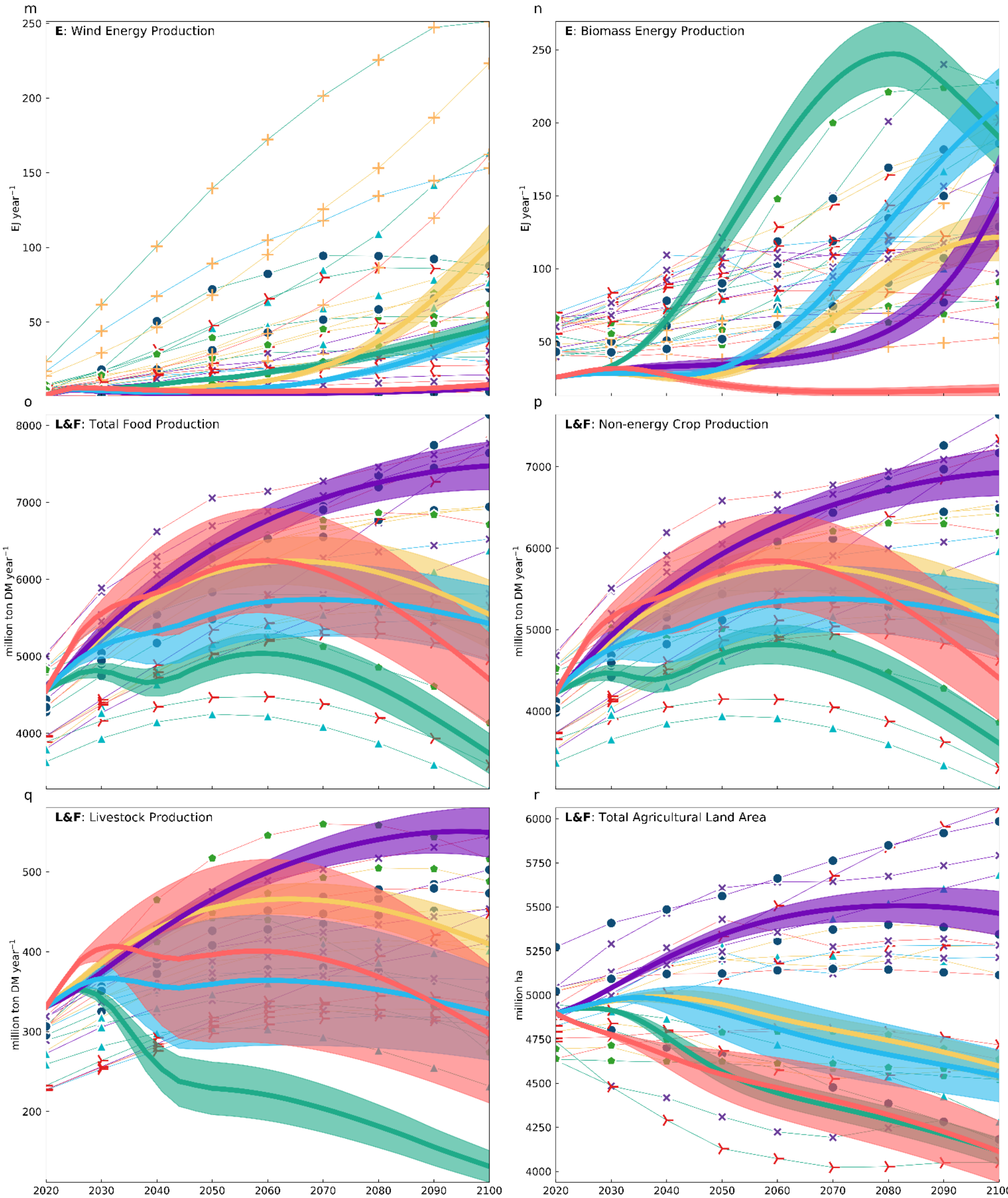


a
SE: Total Population
billion
b
SE: Primary Education Graduates
million
c
SE: Secondary Education Graduates
million
d
SE: Tertiary Education Graduates
million
e
SE: GWP per Capita
$1000 year^{-1}person^{-1}
f
E: Total Renewable Energy Production
EJ year^{-1}
2020
2030
2040
2050
2060
2070
2080
2090
2100

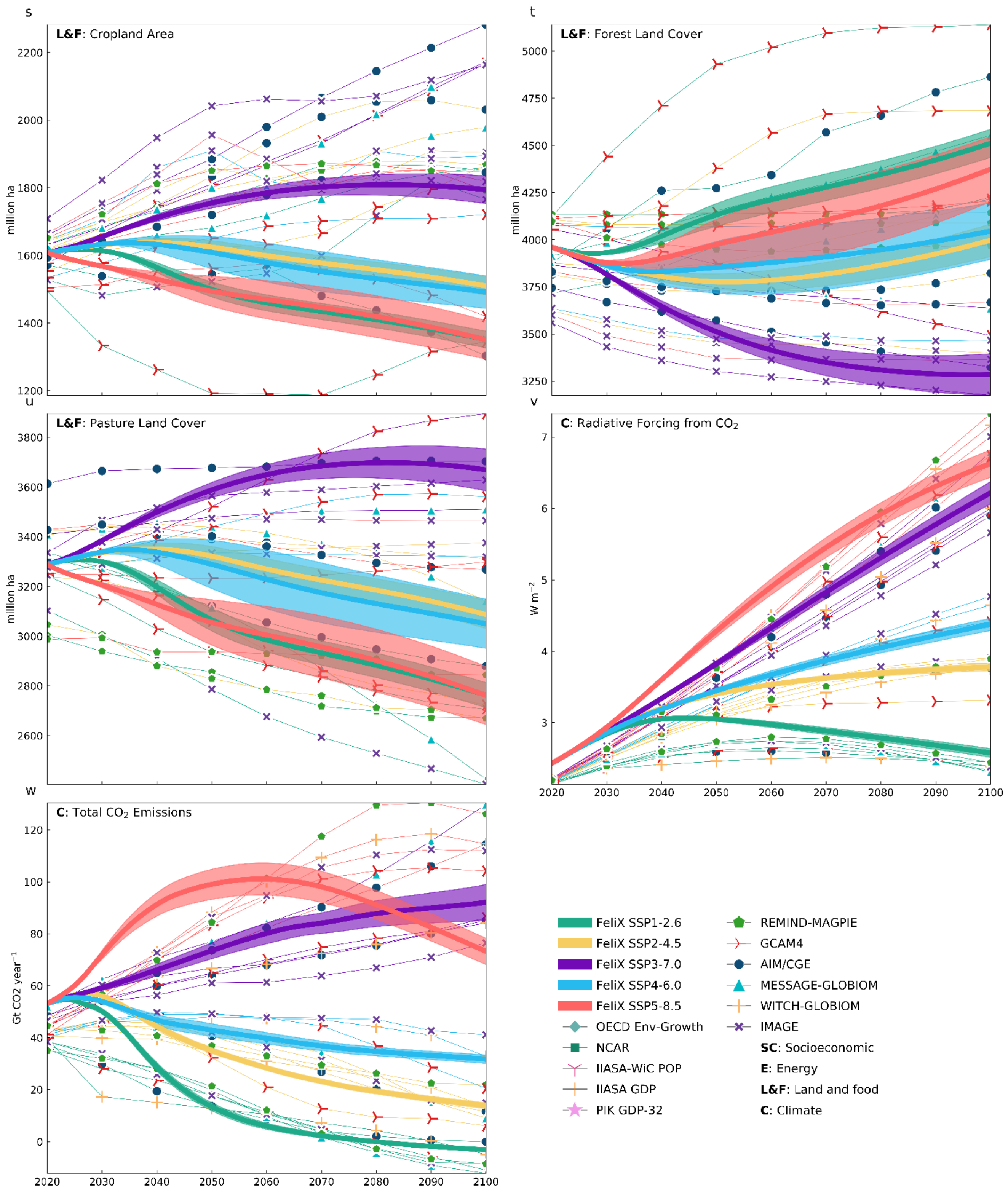
Continued.


g
E: Total Fossil Energy Production
h
E: Energy Demand
i
E: Coal Energy Production
j
E: Gas Energy Production
k
E: Oil Energy Production
l
E: Solar Energy Production
EJ year^{-1}
2020
2030
2040
2050
2060
2070
2080
2090
2100

Continued.


m
E: Wind Energy Production
EJ year⁻¹
250
200
150
100
50
n
E: Biomass Energy Production
EJ year⁻¹
250
200
150
100
50
o
L&F: Total Food Production
million ton DM year⁻¹
8000
7000
6000
5000
4000
p
L&F: Non-energy Crop Production
million ton DM year⁻¹
7000
6000
5000
4000
q
L&F: Livestock Production
million ton DM year⁻¹
500
400
300
200
r
L&F: Total Agricultural Land Area
million ha
6000
5750
5500
5250
5000
4750
4500
4250
4000
2020
2030
2040
2050
2060
2070
2080
2090
2100

Continued.



Supplementary Figure 2. Scenario projections with the FeliX model and their comparison with the projections of major demographic and economic models (Dellink *et al.*, 2017; Samir & Lutz, 2017) and integrated assessment models (Bauer *et al.*, 2017; Calvin *et al.*, 2017; Fujimori *et al.*, 2017; Kriegler *et al.*, 2017; Popp *et al.*, 2017; Riahi *et al.*, 2017; van Vuuren *et al.*, 2017). Projections cover the period 2020-2100 with an annual time step.

Supplementary Table 1. Qualitative assumptions of scenarios

SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP4-6.0	SSP5-8.5
Socioeconomic				
Population growth (Samir & Lutz, 2017)				
Low population growth	Moderate population growth	High population growth	Moderate population growth	Low population growth
Educational attainment (Samir & Lutz, 2017)				
Low number of primary and secondary graduates by the end of century (due to declining population) but high number of tertiary graduates	Moderate number of primary, secondary, and tertiary graduates	High number of primary and secondary graduates but low number of tertiary graduates	High number of primary and secondary graduates but relatively low number of tertiary graduates	Low number of primary and secondary graduates by the end of century (due to declining population) but high number of tertiary graduates
Economic growth (Cuaresma, 2017; Dellink et al., 2017)				
Relatively high economic growth which is tempered over time to balance with well-being, equity, and sustainability	Moderate economic growth following historical patterns	Low economic growth due to limited international cooperation, low investments in education	Relatively low economic growth globally due to unequal progress between high- and low-income countries.	High economic growth that is much focused on consumerism and resource-intensive consumption
Energy				
Energy demand and market share of renewable and fossil fuels (Bauer et al., 2017; O'Neill et al., 2017)				
Low energy demand; high, relatively high, and moderate market share for solar, biomass, and wind; low market share for all fossil energies	Relatively high energy demand; relatively high, low, and high market share for solar, biomass, and wind; moderate, moderate, and high market share for coal, gas, and oil	Moderate energy demand; low, high, and low market share for solar, biomass, and wind; relatively high, relatively low, and moderate market share for coal, gas, and oil	Moderate energy demand; moderate market share for solar, biomass, and wind; relatively low, low, and moderate market share for coal, gas, and oil	High energy demand; relatively high, low, and relatively high market share for solar, biomass, and wind; relatively high, high, and high market share for coal, gas, and oil
Energy technology advances (fossil fuels recovery and exploration technology and renewable technology investment and efficiency) (Bauer et al., 2017; O'Neill et al., 2017)				
Fast renewable energy technology improvement, and limited fossil energy technology improvement (both efficiency and investment)	Moderate renewable and fossil energy technology improvement (both efficiency and investment)	Slow renewable and fossil energy technology improvement (both efficiency and investment)	Relatively slow renewable and fossil energy technology improvement (both efficiency and investment)	Moderate renewable energy technology improvement and fast fossil technology improvement (both efficiency and investment)
Investment in fossil fuels and their resource availability, renewable production cost reduction, limit on emissions from fossil fuels (Bauer et al., 2017; O'Neill et al., 2017)				
High, relatively high, and moderate solar, biomass, and wind energy production; low energy production for all fossil fuels; low emissions and radiative forcing	Relatively high, low, and high solar, biomass, and wind energy production; moderate, moderate, and high coal, gas, and oil energy production; relatively high emissions and radiative forcing	Low, high, and low solar, biomass, and wind energy production; relatively high, relatively low, and moderate coal, gas, and oil energy production; relatively high emissions and radiative forcing	Moderate solar, biomass, and wind energy production; relatively low, low, and moderate coal, gas, and oil energy production; moderate emissions and relatively high radiative forcing	Relatively high, low, and relatively high solar, biomass, and wind energy production; relatively high, high, and high coal, gas, and oil energy production; high emissions and radiative forcing

Continued.

Land				
Land-use change (Jiang & O'Neill, 2017; O'Neill et al., 2017; Popp et al., 2017)				
Low land cover built-up area; deforestation at a slow rate and the expansion of cropland and pasture land at a slow rate	Relatively low land cover built-up area; deforestation at a moderate rate and the expansion of cropland and pasture land at a moderate rate too	Low land cover built-up area; deforestation at a high rate and the expansion of cropland and pasture land at a high rate too	Relatively low land cover built-up area; deforestation at a moderate rate and the expansion of cropland and pasture land at a moderate rate too	High land cover built-up area; deforestation at a relatively slow rate and the expansion of cropland and pasture land at a relatively slow rate too
Land productivity growth (O'Neill et al., 2017; Popp et al., 2017)				
High crops and livestock yield	Moderate crops and livestock yield	Low crops and livestock yield	Relatively low crops and livestock yield	Relatively high crops and livestock yield
Food and diet change				
Food waste, food consumption, diet change (Eker et al., 2019)				
Low waste, low plant foods consumption, low animal foods consumption, more sustainable diets	Waste at the current level, moderate plant and animal foods consumption, the global diet follows the status quo (more meat, less vegetables)	Relatively high waste, moderate plant and animal foods consumption, the global diet follows the status quo (more meat, less vegetables)	Relatively low waste, moderate plant and animal foods consumption, the global diet follows may slightly to towards the less meat, more vegetables	High waste, high plant and animal foods consumption, the global diet follows the status quo (more meat, less vegetables)
Climate				
Climate mitigation policy assumptions				
As an indicative scenario for low-range emissions with the highest potential for mitigation facilitated by technology advances and high level of global cooperation, we assumed carbon pricing for fossil fuel unit cost of production with a linearly increasing (global average) trajectory (reaching ~$450 per tCO_2 by 2100), high land-based mitigations; high adoption of carbon capture and storage for reducing emissions from fossil fuels and from bioenergy (BECCS). To model high global cooperation in adopting climate policies as early as possible, we activated all implemented measures by 2025. For other greenhouse gases that were not modelled endogenously in FeliX, we calibrated the model under the green recovery consistent with the lowest forcing level of 2.6 W $m^{-2,}$ with data from the IASA Scenario Database.	With medium mitigation challenges, we assumed slightly lower carbon price (reaching ~$300 per tCO_2 by 2100) compared to SSP1-2.6, lower adoption of carbon capture and storage for reducing emissions from fossil fuels and also from bioenergy (BECCS), and also lower land-based mitigations. To indicate less global cooperation in adopting climate policies, all measures were implemented by 2040, later than SSP1-2.6. For other gases, we calibrated the model consistent with 4.5 W m^{-2} forcing level, with data from the IASA Scenario Database.	With significant challenges to mitigation (and also with little global cooperation in the former), we assumed no effective climate policy regime for carbon emissions in FeliX. For other gases, we calibrated the model consistent with 7.0 W m^{-2} forcing level, with data from the IASA Scenario Database.	Similar to SSP2.4.5, with medium mitigation challenges, we assumed slightly lower carbon price (reaching ~$300 per tCO2 by 2100) compared to Green Recovery, lower adoption of carbon capture and storage for reducing emissions from fossil fuels and also from bioenergy (BECCS), and also lower land-based mitigations. For other gases, we calibrated the model consistent with 6.0 W m-2 forcing level, with data from the IASA Scenario Database.	With significant challenges to mitigation (and also with little global cooperation in the former), we assumed no effective climate policy regime for carbon emissions in FeliX. For other gases, we calibrated the model consistent with 8.5 W m^{-2} forcing level, with data from the IASA Scenario Database.

Supplementary Table 2. The list of candidate uncertain model parameters used for sensitivity analysis.
See the Supplementary Table 2 in the Excel spreadsheet with this article.

Supplementary Table 3. Key scenario parameters and their quantification in the FeliX model.
See the Supplementary Table 3 in the Excel spreadsheet with this article.

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