Scenario modelling of the sustainable development goals under uncertainty

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Key Points (140 characters)

- We articulate methodological steps in scenario modelling to enhance sustainability assessment under future uncertainty.
- We illustrate the sensitivity of sustainable development goals to global scenarios and their many plausible realisations.
- We show that a greater diversity of models ought to be used for sustainability analysis to better address complexity and uncertainty.

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Abstract

Models are increasingly used to inform the transformation of human-natural systems towards a sustainable future, aligned with the United Nations Sustainable Development Goals (SDGs). However, the future uncertainty and complexity of alternative socioeconomic and climatic scenarios challenge the model-based analysis of sustainable development. Obtaining robust insights, which can remain valid under a larger diversity of plausible futures, 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 Earth and human interactions. Here, we quantify and explore the impacts of model uncertainty and structural complexity on the projection of global change scenarios for sustainable development. We implement the Shared Socioeconomic Pathways and the Representative Concentration Pathways in a feedback-rich, integrated assessment model of system dynamics. With our model's broad scope for SDG analysis, we evaluate the impacts of these scenarios on the global trajectories of 16 sustainable development indicators related to food and agriculture, well-being, education, energy, economy, sustainable consumption, climate, and biodiversity conservation under uncertainty. The results show internally consistent (across sectors), yet quantitatively different (compared to other models) realisations of reference scenarios. They also demonstrate the sensitivity of sustainability indicators to reference global scenarios, driven by the complex and uncertain multisectoral dynamics that underlay the SDGs. These results highlight the importance of enumerating global scenarios and their uncertainty exploration with a diversity of models of different input assumptions and structures to capture a wider variety of future possibilities in planning for sustainability.

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 (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 (MSD) (Jafino *et al.*, 2021; Quinn *et al.*, 2020), or transitions models (Köhler *et al.*, 2018), have been effectively used to systematically analyse the interactions of conflicting, inter-connected sustainability priorities in complex human-natural systems (Quinn *et al.*, 2017; Trindade *et al.*, 2017) and to navigate actionable compromises between competing agendas (Gold *et al.*, 2019; Hadjimichael *et al.*, 2020). These modelling efforts aim to advance the understanding and analysis of human-natural 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 (Sterman *et al.*, 2012), and bottom-up agent-based models (Moallemi & Köhler, 2019). Modelling applications have also spanned different aspects of the SDGs such as food and diet (Bijl *et al.*, 2017; Eker *et al.*, 2019; Malek *et al.*, 2020), 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), and biodiversity conservation (Mace *et al.*, 2018). Models have also assessed the nexus of (often limited) interacting SDGs 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 (Randers *et al.*, 2019). 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 coupled human-natural systems where subsystems experience non-linear interactions, irreversible changes, and tipping points in their evolution (Lempert *et al.*, 2003).

To address these challenges, past studies have often used *scenarios*, quantified by a set of integrated assessment models (Riahi *et al.*, 2017), to explore the plausible trajectories of system behaviour according to different sets of assumptions about the future (Guivarch *et al.*, 2017; Lamontagne *et al.*, 2018; 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 with 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 Section 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 *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 (Lamontagne *et al.*, 2019; 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 these 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. For example, 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) is perhaps the most prominent example which evaluated a selected number of SDGs under two SSP scenarios as well as under previously developed global change scenarios (Parkinson *et al.*, 2019; van Vuuren *et al.*, 2015) using two marker models of IMAGE (van Vuuren *et al.*, 2017) and MESSAGE-GLOBIOM (Fricko *et al.*, 2017). The broader use of SSPs and RCPs framework in other research domains such as sustainable development is crucial for developing a more comprehensive and consistent account of possible integrated futures and 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., feedback-rich, system dynamics models (Walsh *et al.*, 2017)), is important to expand the scenario space around SSPs and RCPs and to capture a wider set of futures in the global scenario framework, driven by different perspectives and model uncertainties (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 and the emergence of new, open-source integrated assessment models (e.g., FeliX (Walsh *et al.*, 2017), Earth3 (Randers *et al.*, 2019), see the 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 develop a methodology, supported by computational techniques from *exploratory modelling*, that allows the implementation of global scenario frameworks and their uncertainty exploration with new integrated assessment models for sustainable development.

Exploratory modelling, originally pioneered at the RAND Corporation (Bankes, 1993; Hodges, 1991; Hodges & Dewar, 1992; Lempert *et al.*, 2003), is specifically concerned with dealing with uncertainty and complexity in models. The central idea of exploratory modelling is to move from the notion of a good model with an accurate prediction of the most likely futures to an *ensemble of models* as a thinking aid for enumerating and testing a range of possible assumptions via computational experiments (Moallemi *et al.*, 2020a). Exploratory modelling can be adopted for sustainability analysis with contributions to answer *decision support* questions, illuminating robust policy choices and supporting adaptation plans under deep uncertainty (Gold *et al.*, 2019; Trindade *et al.*, 2019; Wise *et al.*, 2014). There are several examples of exploratory modelling for decision support and in relation to various SDGs, from water (Trindade *et al.*, 2020), to energy (Moallemi *et al.*, 2017), to critical infrastructure (Hall *et al.*, 2019), to food (Eker *et al.*, 2019), and to climate mitigation (Lamontagne *et al.*, 2019), as recently reviewed by Moallemi *et al.* (2020a) and Herman *et al.* (2020). Exploratory modelling can be also used to inform *theory testing and model development*, aiming to explore less explicit forms of uncertainty in model structures (e.g., relationships, equations) and uncertainty in their underpinning theories and conceptual foundations. This also corresponds to Bankes (1993) model-driven analysis that aims to reveal irregularities of behaviour and output patterns of several models of the same phenomenon, without reference to a policy question (de Haan *et al.*, 2016). This application of exploratory modelling is, however, a less discussed area which we leverage in this article. A model-driven exploratory analysis allows us to investigate the impacts of a new model's structural complexity and its uncertainty space on global change scenario projections and to assess how and whether new models might be useful in better understanding the future. This will advance previous scenario modelling efforts by generating new realisations of global reference scenarios, resulted from non-marker models of new feedback structures and complexity, for sustainable development.

To demonstrate our methodology, we implement the SSP and RCP scenarios in the Functional Enviro-economic Linkages Integrated neXus (FeliX) (Eker *et al.*, 2019; Walsh *et al.*, 2017) model, a globally aggregate and feedback-rich integrated assessment model of Earth and human interactions based on the system dynamics approach (Sterman, 2000) (Sections 2.1 and 2.2). We analyse global trajectories of 50,000 different realisations under five plausible combinations of SSPs and RCPs (i.e., 10,000 each) (Sections 2.3 to 2.6). We evaluate 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 (Section 3.1) and analyse in what areas and to what extents they diverge from previous projections to highlight the value added of exploring the implications of new models for global scenarios (Section 3.2). We also assess 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) (Section 3.3). This application provides in-depth insights into the achievement of the global SDGs under a larger scenario space.

2 Methods

We selected 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 generate the diversity of output behaviours in response to the model's structural complexity, 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).

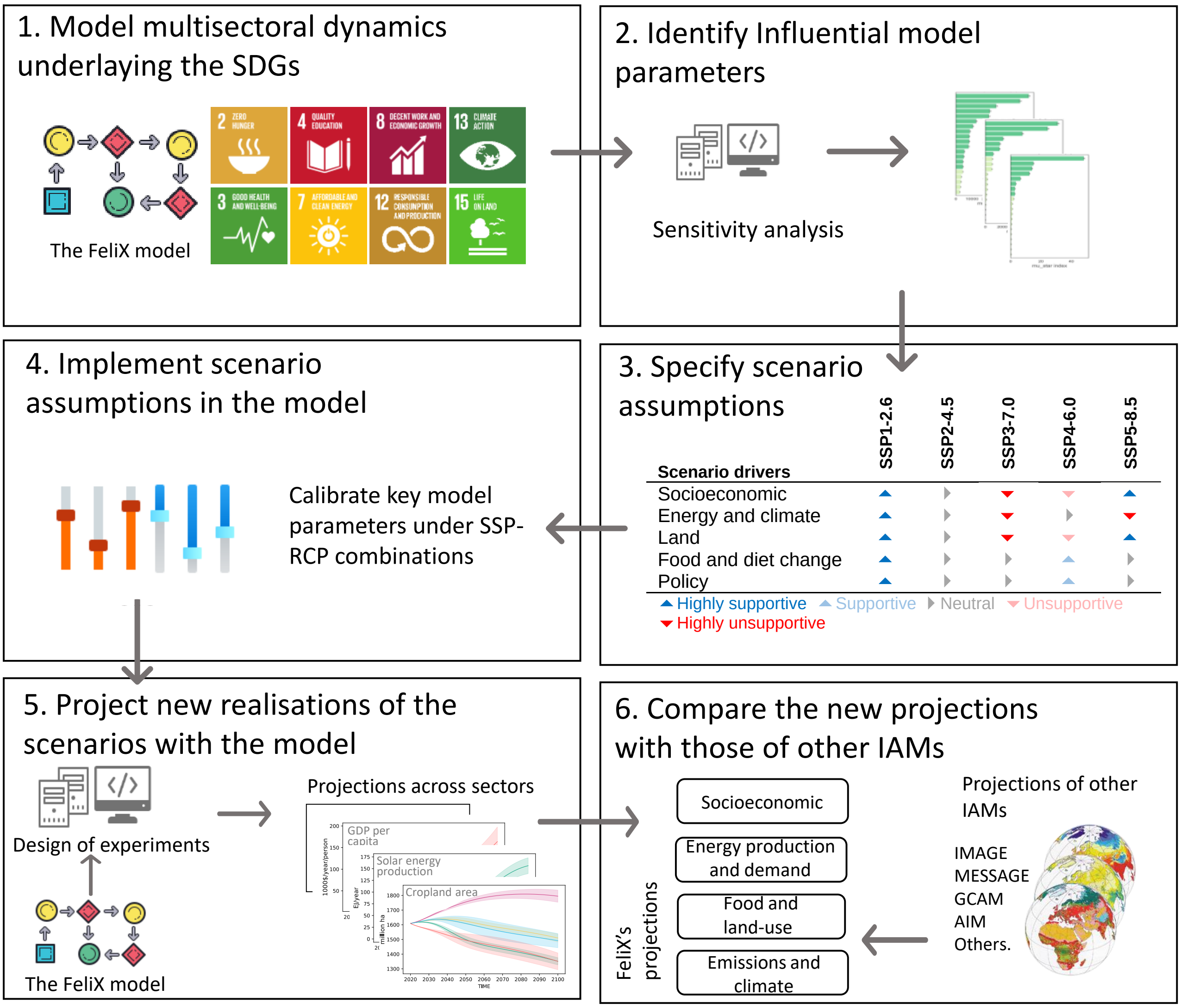

Figure 1. Overview of methodological steps for implementing global scenario frameworks in a new integrated assessment model for sustainable development.

2.1 Model multisectoral dynamics underlaying SDGs

In the first step, we modelled anthropogenic processes of the multisectoral dynamics that drive SDG progress through an integrated assessment model of Earth and human interactions called FeliX (Figure 2). FeliX simulates complex feedback interactions via a nexus of societal and biophysical sub-models, enabling the analysis of non-linearities, tipping points, and abrupt changes in several SDG trajectories. The model is based on the system dynamics approach (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). 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 compared to previous studies (Gao & Bryan, 2017; Obersteiner *et al.*, 2016; Randers *et al.*, 2019; van Vuuren *et al.*, 2015). 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. Each sub-model includes feedback interactions between several model components necessary to generate complex interactions underlaying the SDGs.

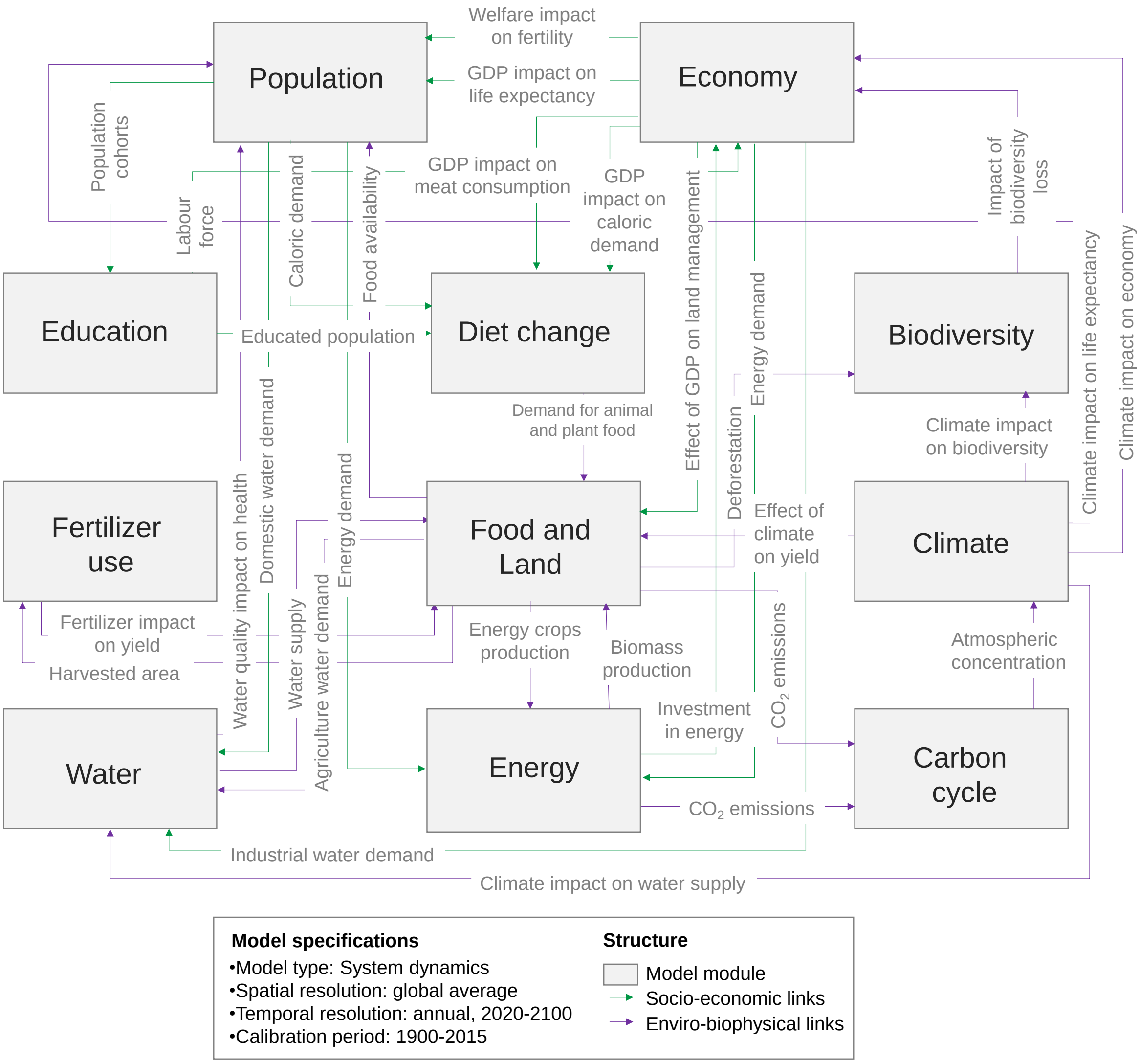

Figure 2. The overview of the FeliX model. Adapted from and updated based on Rydzak *et al.* (2013).

- *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.

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 fertility and the risk of polluting nutrient surplus.	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.		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

In the second step, we identified influential model parameters for FeliX to be used in the scenario modelling process. 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. Exploratory modelling can reappropriate methods from sensitivity analysis (Jaxa-Rozen & Kwakkel, 2018; Lamontagne *et al.*, 2018) to prioritise influential parameters contributing to model uncertainties (i.e., factor prioritisation (Gao *et al.*, 2016)) and to identify those parameters with the least impacts in scenario modelling (i.e., factor fixing (Saltelli *et al.*, 2008)), among other reasons (e.g., factor mapping or scenario discovery (Guivarch *et al.*, 2016)). This adoption of sensitivity analysis in exploratory modelling differs from the traditional purposes of improving model structure (Iman *et al.*, 2005) or specifying the change direction in model behaviour (Anderson *et al.*, 2014). Rather, it aims to generate only important and consequential scenarios driven by the variation of influential parameters and the exclusion of trivial parameters (which could lead to the poor identifiability of generated scenarios in relation to input parameters). This shares the core idea of exploratory modelling in systematically analysing the implications of various input uncertainties in the outcome space before deciding about their inclusion or exclusion in scenario modelling.

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) (Figure 3). 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; Herman *et al.*, 2013). 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).

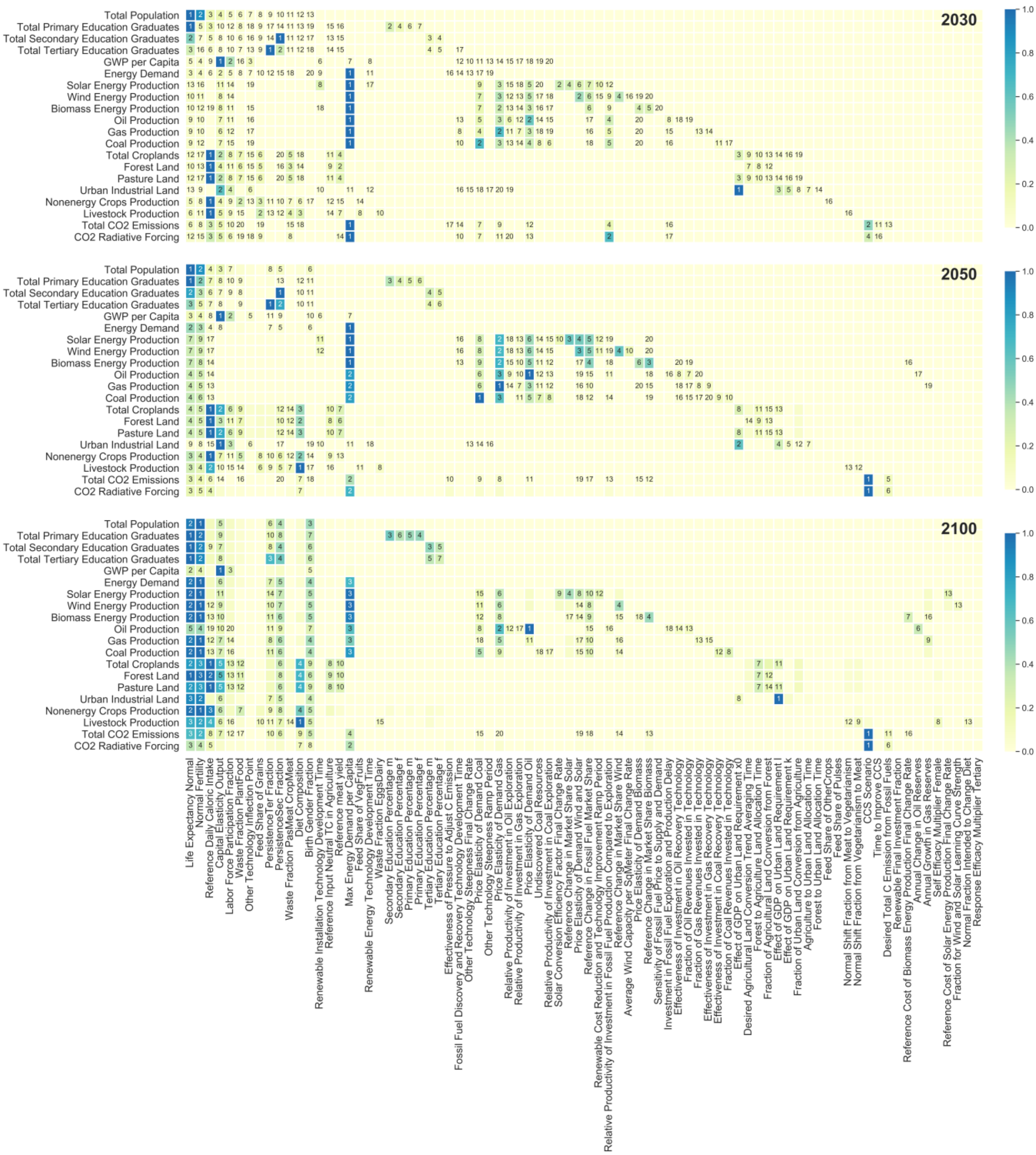

Figure 3. The ranking of influential model parameters. Sensitivity is the normalised values of Morris index μ^* between 0 and 1. For each output variable (y axis), the most influential input parameters (x axis) are annotated with their rank. Information on the unit and definition of each parameter is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

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 (see Supplementary Methods for details). 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 (Hadjimichael, 2020).

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.

2.3 Specify scenario assumptions

In the third step, we identified and described *a priori* 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), called the Shared Socioeconomic Pathways (SSPs) (O'Neill *et al.*, 2017; Riahi *et al.*, 2017) and the Representative Concentration Pathways (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 ℃ 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 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 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 to SSPs 2, 3, and 4 (respectively). We excluded RCP 1.9 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 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 too. 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. We also 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 consistenmcy 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

In the fourth step, we translated our scenario assumptions (Section 2.3) into influential model parameters (Section 2.2) for FeliX. 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; Lamontagne *et al.*, 2018; 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 (Bankes, 1993).

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.

2.5 Project scenario realisations with the model

In the fifth step, 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 used the design of experiments exploratory modelling (Herman *et al.*, 2020) to sample deeply uncertain scenario assumptions that strongly influence the future. Design of experiments simulates and evaluates 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, known as a *state of the world (SOW)*.

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; Kasprzyk *et al.*, 2013). 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).

In projecting scenarios with the design of experiments, 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 (Section 2.4) and their uncertainty space, we simulated the global trajectories of socioeconomic, energy, climate, and land and food sectors in 23 control variables 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 (Section 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 combination. This comparison did not aim for agreement with other models, and was rather focused on differences (due to the new model structural complexity) and the new insights we arrived at that would not have been possible without exploratory modelling with a greater diversity of models.

3 Results and discussion

3.1 New 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 this scenario (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. 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) created a high potential for mitigation with low-range emissions (Figure 4w) and low radiative forcing levels (Figure 4v) by 2100.

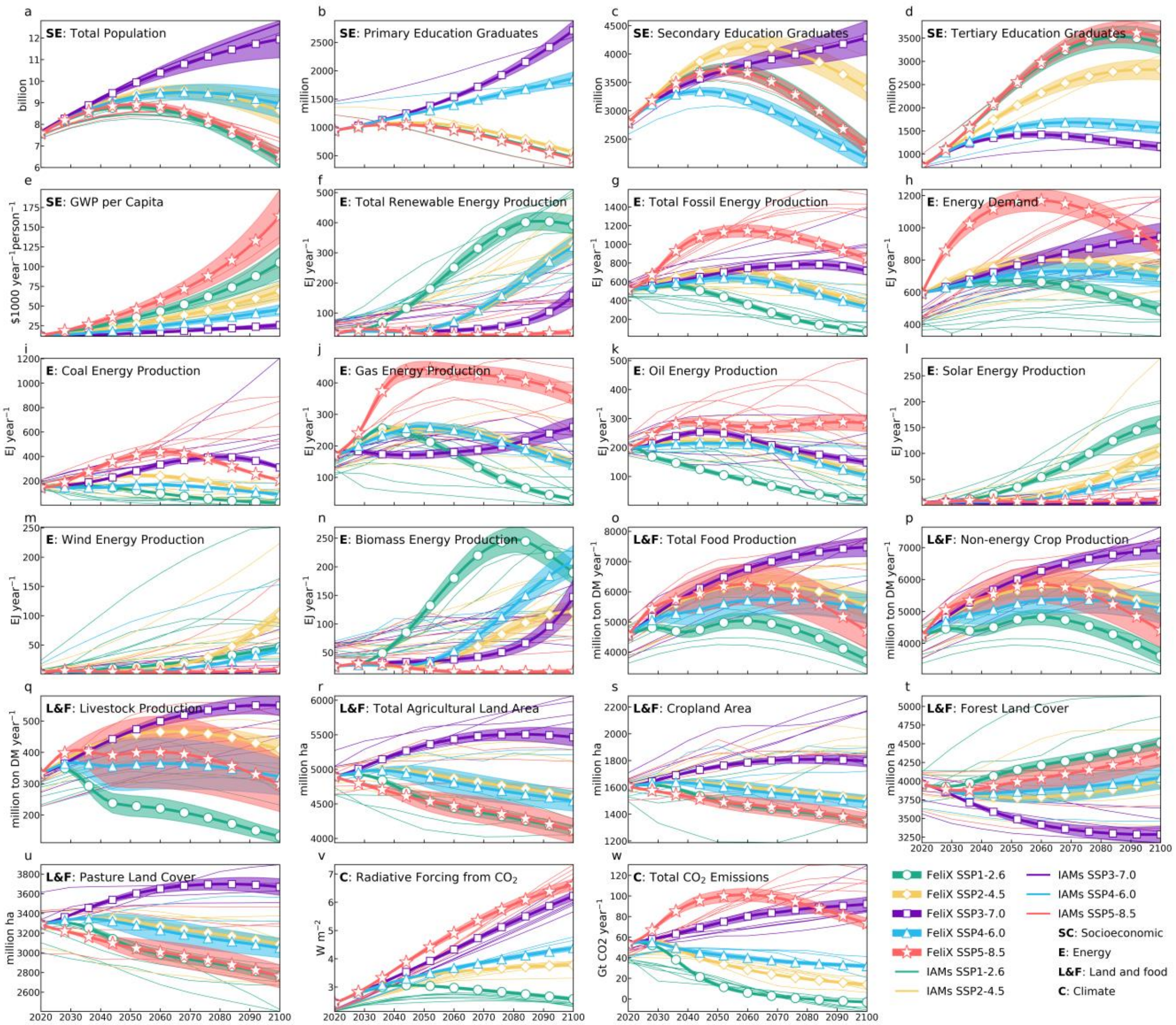

Figure 4. Scenario projections with the FeliX model (envelopes) and their comparison with the projections of major demographic and economic models (Dellink *et al.*, 2017; Samir & Lutz, 2017) and integrated assessment models (Bauer *et al.*, 2017; Calvin *et al.*, 2017; Fujimori *et al.*, 2017; Kriegler *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 than 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 this scenario.

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 than other scenarios to meet the increasing energy demand (Figures 4i to 4k). In the food and land sector (Figures 4o to 4u), a small yet high animal-calorie-consuming population resulted in crop and livestock production lower than the business-as-usual but still higher than the SSP1-2.6 scenario. 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 among all scenarios, creating significant challenges to mitigation (Figures 4v and 4w).

3.2 Divergence from standard projections

The exploratory 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 (Section 2.1) and different parametrisation (Section 2.4). This highlighted the new insights that would not have been possible without exploring the projections of our non-marker model. 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 standard 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). Similar variations, resulting from differing model structural complexity and parameterisation, were also 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' storyline narratives (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 model module 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 was 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 links 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 underlay 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 help to 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).

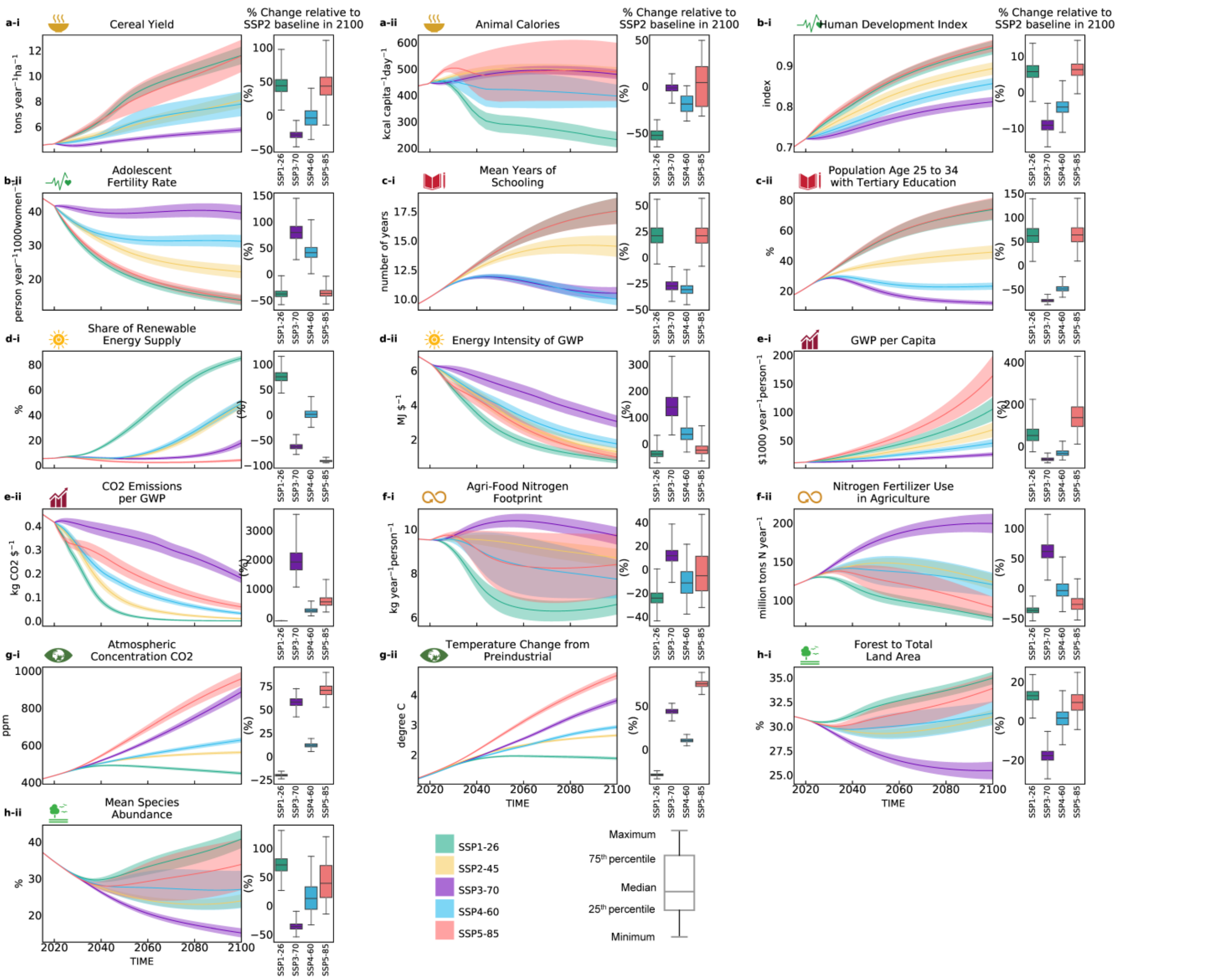

Figure 5. The implications of modelled scenarios for sustainable development across 50,000 SOWs and in 16 indicators. In each subplot, the envelope plots show each indicator's trajectory across five scenarios with descriptive statistics (mean and standard deviation) to represent the average projected 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 21^{st} 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 Sections 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. 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.

We used a methodology, inspired by model-driven exploratory analysis, to implement global scenarios in a non-marker integrated assessment model and to investigate the new uncertainty of future projections. The methodology was the key and a generalisable contribution, enabling a greater diversity of models to be adopted for SDG analysis. It helped expand the limits of benchmark scenarios through the exploration of a larger uncertainty space driven by models. We projected new realisations of future scenarios with the non-maker model across population, economy, energy, land, food, and climate systems from 2020 to 2100, and highlighted the new insights (e.g., diet change impacts). Our study also contributed to sustainability science by enabling a wider adoption of global scenarios to explore their broader implications beyond the original foci of climate change and in sustainable development across 16 indicators by 2030 and beyond.

While our proposed methodology enabled the parameterisation of an integrated assessment model to evaluate SDG trajectories under global scenarios, it did not measure the actual progress towards explicit targets nor discover the individual contribution of socioeconomic (SSP) versus climatic (RCP) drivers in achieving these targets. An important next step in the further development of our methodology for SDG analysis is to adopt post-processing techniques (e.g., scenario discovery cluster analysis (Guivarch *et al.*, 2016; Rozenberg *et al.*, 2014)) to identify *a posteriori* 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 also explored the prevalent uncertainty of several indicated model parameters in this paper, 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, such as scenario discovery (Hadjimichael *et al.*, 2020), robustness analysis (Gold *et al.*, 2019; Herman *et al.*, 2020), and adaptive policy-making (Trindade *et al.*, 2020), 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.

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 has 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.

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, regional, or national scales (Szetey *et al.*, 2021). However, large scale and global scenarios, in reality, translate into *local* changes in human interactions with the environment. 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 (Bennett *et al.*, 2021; Moallemi *et al.*, 2020b). 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 gender inequality (Emmerling & Tavoni, 2021) and the representation of heterogeneous actors (Ilkka *et al.*, 2021). Future work on integrated assessment modelling, therefore, requires capturing the societal dynamics of lower scales beyond the currently global, regional, or national assumptions to better incorporate them in scenario exploration (Liu *et al.*, 2013). This can lead to more reliable insights that can account for the diversity of local priorities and the heterogeneities in the availability of skills and resources across regions, enabling a more just and inclusive sustainable development by tailoring the plans to the unique socio-ecological characteristics of each context.

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Code and Data Availability

The datasets/code generated during this study are available from https://doi.org/10.5281/zenodo.4973856. 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; Twitter: @EnayatMoallemi).

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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