Scenario modelling of the sustainable development goals under uncertainty

Enayat A. Moallemi[1,2,3,*], Lei Gao[4,†], Sibel Eker[5,†], Brett A. Bryan[1,†]

[1]Centre for Integrative Ecology, School of Life and Environmental Sciences, Deakin University, Melbourne, Australia.

[2]Monash Sustainable Development Institute, Monash University, Melbourne, Australia.

[3]The 4TU Centre for Resilience Engineering, the Netherlands.

[4]The Commonwealth Scientific and Industrial Research Organisation (CSIRO), Waite Campus, Urrbrae, Australia.

[5]International Institute for Applied Systems Analysis, Laxenburg, Austria.

* Corresponding author: Enayat A. Moallemi (e.moallemi@deakin.edu.au)

[†] These authors contributed equality.

Key Points (140 characters)

- Articulating methodological steps in scenario modelling can help researchers enhance sustainability assessment under future uncertainty.
- Using a new methodology, we illustrate the sensitivity of sustainable development goals to global scenarios and their uncertainties.
- The results show that achieving ambitious targets requires substantial progress in socioeconomic and environmental indicators.

Author Contributions

Conceptualization: E. A. Moallemi
Data curation: E. A. Moallemi, S. Eker, L. Gao
Formal Analysis: E. A. Moallemi, S. Eker, L. Gao, B. A. Bryan
Funding acquisition: B. A. Bryan
Investigation: E. A. Moallemi, S. Eker, L. Gao, B. A. Bryan
Methodology: E. A. Moallemi, S. Eker, L. Gao
Visualization: E. A. Moallemi
Writing – original draft: E. A. Moallemi
Writing – review & editing: E. A. Moallemi, S. Eker, L. Gao, B. A. Bryan

Abstract

Models are increasingly used to inform the transformation of human-natural systems towards more sustainable futures, aligned with the United Nations Sustainable Development Goals (SDGs). However, the future uncertainty of alternative socioeconomic and climatic scenarios challenges the model-based analysis of sustainable development. Obtaining robust insights, which can remain valid under many plausible futures, requires a systematic processing of uncertainty through scenario modelling. Here, we use exploratory modelling—an approach for exploring the implications of various modelling assumptions using computational experiments—to quantify and analyse the impacts of global socioeconomic and climate uncertainties in achieving SDGs. We develop a systematic, computational methodology to guide researchers in coping with future uncertainty in sustainable development, consistent with global benchmark scenario frameworks. To demonstrate, we implement the global climate and sustainability scenarios, namely the Shared Socioeconomic Pathways and the Representative Concentration Pathways, in an integrated assessment model for evaluating the global trajectories of eight SDGs related to sustainable food and agriculture, health and well-being, quality education, clean energy, sustainable economic growth, climate action, and biodiversity conservation under uncertainty. The results show that the progress towards different goals is highly sensitive to the modelled scenarios and to their uncertainty specification. This sensitivity highlights the importance of enumerating the diversity of alternative scenarios and their uncertainty exploration to enable a comprehensive assessment of sustainable development with the consideration of performance across a range of plausible futures and their boundary conditions. The enhanced modelling of scenarios can help prepare for 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). The achievement of 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 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 different competing agendas (Gold *et al.*, 2019; Hadjimichael *et al.*, 2020).

A diverse set of models have 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), integrated assessment models (van Beek *et al.*, 2020), bottom-up agent-based models (Moallemi & Köhler, 2019), and transitions models (Köhler *et al.*, 2018). 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 multiple interacting SDGs such as food-energy-water (Van Vuuren *et al.*, 2019), land-food (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). Past studies have often used *scenarios* to explore these uncertainties through 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 2.2).

The future development of energy, land-use, and emissions sectors according to the SSPs and RCPs has been extensively characterised and expanded, using a set of five *marker* integrated assessment models (IAMs) 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). 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. 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 the SDGs 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 integrated assessment models with different sets of input and structural assumptions has been rare. Among the few applications of new models is Allen *et al.* (2019) who used four SSPs as a benchmark 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 using their new systems model. 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, 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 the systematic treatment of uncertainty, aligned with global projections, in new domains (such as the SDGs) as well as the expansion of the uncertainty exploration of current scenario frameworks (such as the SSPs and RCPs) with new integrated assessment models. Addressing these gaps has become more important in recent years especially given the increasing use of models for 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 need to comprehensively handle and appropriately treat future uncertainty in line with benchmark global projections.

Here, we develop a methodology supported by computational techniques from exploratory modelling to quantify global scenario frameworks and to systematically explore their uncertainty space in achieving the SDGs through many possible future realisations. The use of exploratory modelling as an approach which is specifically concerned with dealing with uncertainty and complexity in models is key in enhancing the implementation of these scenarios (Bankes, 2002; Lempert *et al.*, 2003; Moallemi *et al.*, 2020a). This can contribute significantly to method development in modelling for sustainable development under global change. To demonstrate, 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). The adoption of a new model was undertaken to advance previous SSP modelling efforts by exploring model structural complexity and by generating a wider range of future variations of global reference scenarios across marker and non-marker models (Riahi *et al.*, 2017). We analyse global trajectories of 50,000 different realisations under five plausible combinations of SSPs and RCPs (i.e., 10,000 each). 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. We assess 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), climate action (SDG13), and biodiversity conservation (SDG15). This application can provide in-depth insights into the achievement of the global SDGs under a larger scenario space.

2 Methods

2.1 Modelling multisectoral dynamics

We modelled the physical and anthropogenic processes of the multisectoral dynamics that drive SDG progress through an integrated assessment model of Earth and human interactions called FeliX. 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 SDG trajectories. The model is based on the system dynamics approach (Sterman, 2000) and is set at a global scale 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 as 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. The selection of SDGs and their indicators were guided by the model scope with the aim of covering a wide diversity of socioeconomic and environmental dimensions ability of sustainability 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 ten FeliX sub-models of population, education, economy, energy, water, land, food and diet change, carbon cycle, climate, and biodiversity.

Each sub-model includes feedback interactions between several model components necessary to generate time-series estimates for SDG indicators (Table 1). *Population*, as the core sub-model, captures the dynamics of population growth and ageing, and is directly linked to all SDGs through its impacts on energy demand, food consumption, and water use, amongst other factors. *Education* computes the population size of people with primary, secondary, and tertiary education, 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, interacting with all SDGs except for SDG4 (as educational attainment is not modelled in FeliX as a function of economic outputs). *Energy* computes energy demand, and the production of different energy sources and market competition between them, interacting 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 different sectors, interacting mostly with SDG2 through supplying water for agricultural activities and SDG3 by providing quality water for domestic use. *Land*, *Food*, *Diet Change*, and *Biodiversity* are extensively described in the FeliX model documentation (Eker *et al.*, 2019; Walsh *et al.*, 2017). They simulate land-use change, food demand and production, diet shift reflecting the proportion and type of meat in the human diet, and the restoration and extinction of species. 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. Finally, *Carbon Cycle* and *Climate* compute emissions from the land and energy sectors, as well as the atmospheric radiative forcing and temperature change of the emitted CO_2 and their absorption in the ocean. These sub-models also interact with most of the SDGs, such as 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 third 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 Benchmark scenario framework

We explored future socioeconomic and climate scenarios 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 socio-economic development. They include five internally consistent qualitative descriptions (narratives) for plausible changes in human development, economy and lifestyle, policies and institutions, technology, and environment and natural resources, in the 21st century, aligned with different degrees of challenges to mitigation (of the emissions from energy and land-use) and adaptation to climate change. The SSP narratives have been expanded by quantitative projections of energy, land-use, and emissions sectors using a set of global integrated assessment models (Riahi *et al.*, 2017). These projections represent SSP baselines where there is an absence of any climate policies (beyond what is in place today) to limit climate forcing and adaptive capacity. To cover the gap in efforts to reduce emissions, the SSPs are complemented with the greenhouse gas concentration trajectories in the RCP scenario framework. 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).

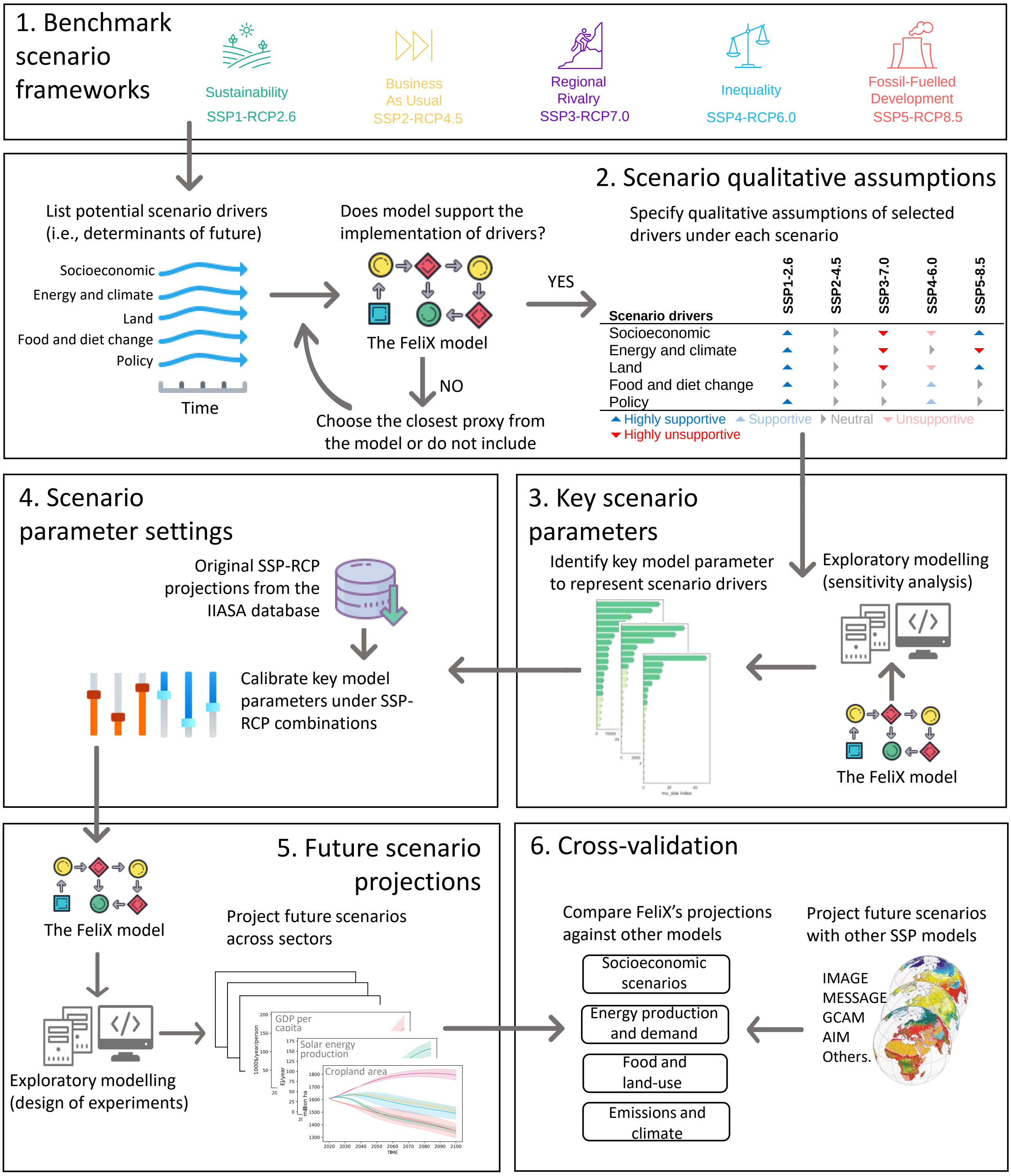

Figure 1. Overview of methodological steps for implementing global scenario frameworks in a new integrated assessment model for SDG analysis.

The SSPs include five socioeconomic futures to 2100: SSP1 (sustainability), SSP2 (business-as-usual), SSP3 (regional rivalry), SSP4 (inequality), and SSP5 (fossil-fuelled development) (O'Neill *et al.*, 2017). The (original) RCPs include 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). Both frameworks in isolation are incomplete by design and are susceptible to uncertainties. The former can only capture societal futures with no direct impacts of climate change and policy responses while the latter only focuses on climate trajectories that are not tied to a specific societal development pathway (O'Neill *et al.*, 2020). The RCPs, therefore, can be combined with the SSPs to specify emissions and concentration assumptions of socioeconomic scenarios and to signal climate policies that are necessary to reach the end of century radiative forcing levels as defined by the RCPs. These combinations provide an integrated approach to explore the space of response options to climate change.

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 (respectively) which focus on highly polluting and sustainable futures. 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). Among these selected integrated scenarios, SSP1-2.6 was the representative of an inclusive and environment-friendly future for sustainable development, SSP2-4.5 was the continuation of past and current trajectories, SSP3-7.0 represented regional rivalry with weak global cooperation and high consumption and environmental footprints, SSP4-6.0 was a world of high inequality in human and economic opportunities, and 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 (Figure 1). 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 FeliX. Such high CRD 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).

2.3 Scenario qualitative assumptions

We elaborated how the future could unfold under each selected SSP-RCP combination in a set of coherent and internally consistent qualitative assumptions about *scenario drivers* over the 21st century. The scenario drivers represent 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). The qualitative assumptions can guide the implementation of scenarios during model calibration and parameterisation (Section 2.5) by providing a detailed account of the expected model behaviour under each scenario. The qualitative assumptions of scenario drivers also provide a context to better understand and interpret model projections in the later steps (Section 2.6).

To specify scenario assumptions, we first enumerated drivers (related to socioeconomic conditions, energy, climate, land, and food and diet change) from the original storylines of the shared socioeconomic pathways (O'Neill *et al.*, 2017) that could potentially be characterised in the FeliX model. However, different model structures do not allow for a precise harmonisation of scenario drivers between various models (as was the case for the five marker models of the shared socioeconomic pathways (Riahi *et al.*, 2017)). Therefore, we adopted only those scenario drivers that could be modelled with FeliX. For example, we did not include 'technology transfer' as a driver given that technology collaborations between countries were not taken into account in our model. We also used '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 'energy technology change' driver from the original shared socioeconomic pathways.

For the selected scenario drivers, we described qualitatively how they can change under each scenario by 2100. The qualitative assumptions 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)). For each scenario driver, we described a range of assumptions under five SSP-RCP combinations (Supplementary Table 1).

Similar to the original SSPs, our scenario assumptions across all drivers represented different degrees of challenges to mitigation (of the emissions from energy and land-use) and adaptation to climate change and their impact 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 climate adaptation and mitigation while the fifth scenario (SSP2-4.5) was representative of moderate mitigation and adaptation challenges.

2.4 Key scenario parameters

Integrated assessment models often have many demographic, macro-economic, and environmental parameters that could be used to specify scenario drivers. However, among these parameters, some may have only trivial impacts on scenario quantification, and therefore should be excluded from parameter settings. This helps avoid over-parametrisation of the model and poor identifiability of model behaviour in relation to input parameters, especially when available data is limited for parameter estimation (Ho *et al.*, 2019). We used *global sensitivity analysis* to identify influential model parameters for scenario drivers (Gao *et al.*, 2016; Saltelli *et al.*, 2008) and ranked them based on their impact (with non-linear interactions) on model outputs. Among the global sensitivity analysis methods, we used Morris elementary effects (Campolongo *et al.*, 2007; Morris, 1991) as a standard technique for screening and ranking influential parameters (Figure 2). Morris elementary effects is a suitable 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). Global sensitivity analysis with Morris elementary effects investigates how variation in model output can be attributed to variation in model inputs. While this can help in ranking model parameters, it does not specify how many of the ranked parameters should be selected for calibration with scenario drivers. We used Latin Hypercube Sampling to test the impact of inclusion or exclusion of different ranked parameters, and to identify and select influential parameters with highest impacts from the ranking results of global sensitivity analysis. See Supplementary Methods for further details about the implementation of this method.

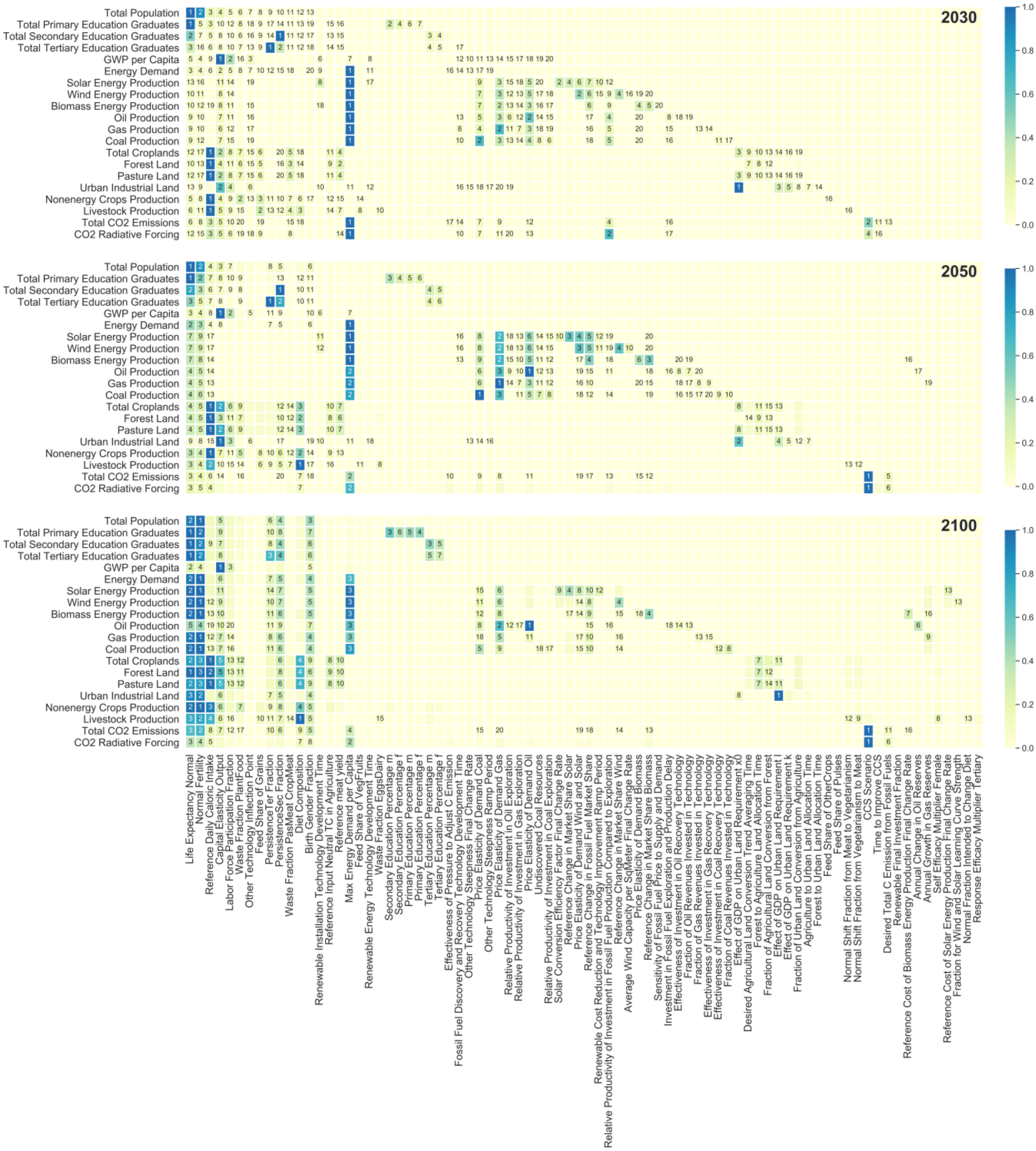

Figure 2. Scenario parameter ranking from global sensitivity analysis results. Sensitivity is the normalised values of Morris index μ^* between 0 and 1. For each output variable (y axis), the most influential input parameters (x axis) are annotated with their rank. Information on the unit and definition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

Figure 2 shows the ranking and selection of important model parameters to be used for calibration with scenario drivers in the projection of different sectors (e.g., population, GDP, energy demand, forest land cover) by 2030, 2050, and 2100. Sensitivity analysis showed a substantial variation in the influence of various drivers. 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). Our finding of key scenario drivers here resonates with the use of socioeconomic (demography, education, economy) factors as underpinning assumptions for scenario projections with other models (Riahi *et al.*, 2017). It is also consistent with considering diet change as a key driver in the transformation of the global food system (Willett *et al.*, 2019) as well as with similar socioeconomic and lifestyle factors that underpinned other food and energy/climate projections using the same FeliX model (Eker *et al.*, 2019; Walsh *et al.*, 2017). We also observed that the influential parameters for each sector do not change significantly over time (Figure 2). Therefore, we used the 2100 ranking results as our reference set for the key scenario parameters to be calibrated in Section 2.5. This choice was also consistent with the SSP assumptions where scenario drivers emerge in the long-term over the 21st century and therefore their long-term sensitivity (by 2100) should be taken into account.

2.5 Scenario parameter settings

The key scenario parameters (Section 2.4) were calibrated consistent with scenario driver assumptions (Section 2.3) and in line with the SSP-RCP projections of marker integrated assessment models (IIASA, 2018). As with the implementation of the SSPs in marker integrated assessment models, we calibrated key parameters related to the demographic and macro-economic drivers of the scenarios, harmonised with the reference demographic and economic model projections of population, (primary, secondary, and tertiary) educational attainment, and GDP, with aggregated (i.e., average of low- and high-income countries) data at the global level (i.e., world average) (Dellink *et al.*, 2017; Samir & Lutz, 2017) (Figure 3). Scenario parameters related to non-socioeconomic drivers (e.g., energy demand, food consumption) were then calibrated consistent with the qualitative assumptions of scenarios (Supplementary Table 1) and the SSP-RCP projections of related sectors by marker integrated assessment models (Figure 3).

2.6 Future scenario projection

Using the parameter setting of each scenario (Section 2.5), we simulated the global trajectories of socioeconomic, energy, climate, and land and food sectors from 2020 to 2100 with the FeliX model. To simulate, we used the *design of experiments* exploratory modelling technique (Herman *et al.*, 2020) to sample deeply uncertain scenario drivers 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 about the value of scenario drivers representing a possible 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 scenario drivers (e.g., population growth, GDP, technology advancement) to create an ensemble of SOWs around each modelled scenario. 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 select 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). 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. 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 ability to generate a diversity of model behaviour (within the range of previous SSP projections produced with the marker integrated assessment model) without excessive computational costs will.

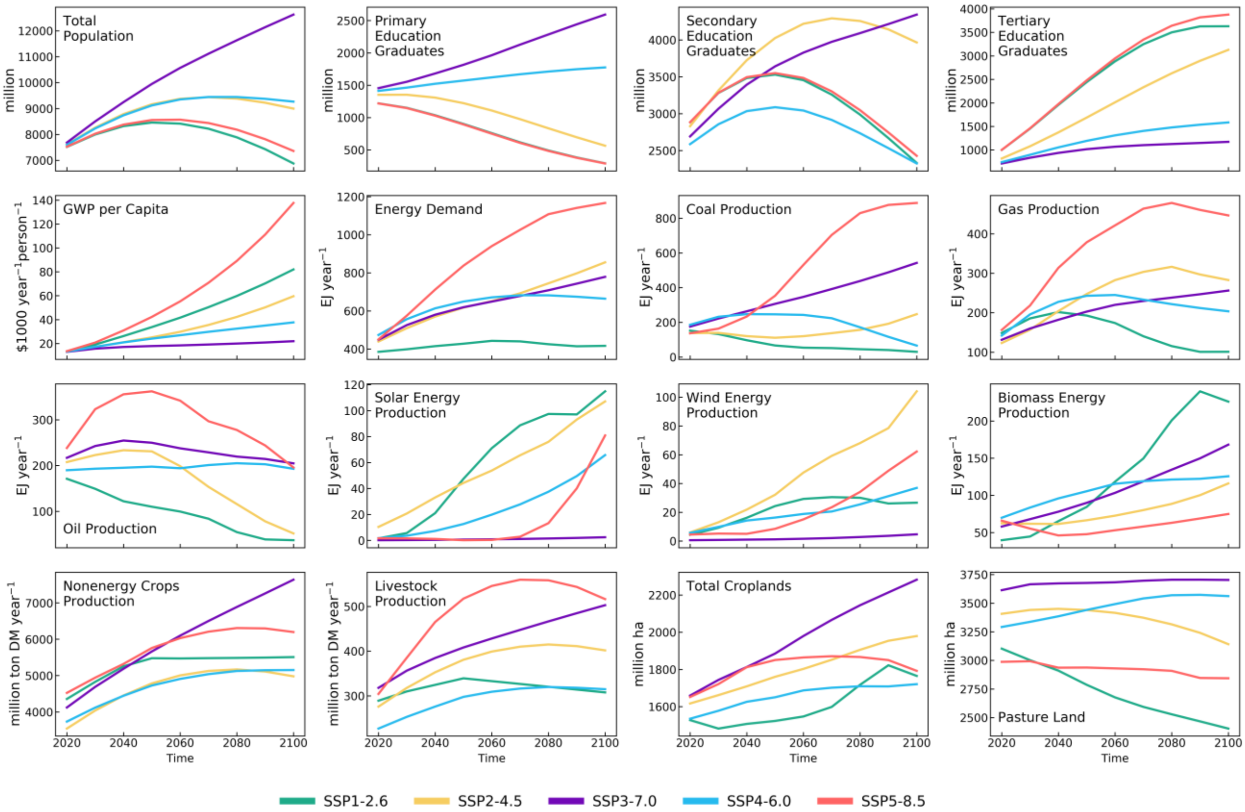

Figure 3. Reference projections of key output variables in socioeconomic, energy, land, and food sectors used in calibration of scenario parameters. The demographic and economic projections in all SSPs are based on the modelling of Samir and Lutz (2017) and Dellink *et al.* (2017), respectively**.** In other energy, land, and food sectors, the SSP1-2.6 projection is based on Bouwman *et al.* (2006); van Vuuren *et al.* (2017), the SSP2-4.5 projection is based on Fricko *et al.* (2017); Riahi *et al.* (2007), the SSP3-7.0 projection is based on Fujimori *et al.* (2017), the SSP4-6.0 projection is based on Calvin *et al.* (2017), and the SSP5-8.5 projection is based on Kriegler *et al.* (2017). Note that the projections of primary education graduates in SSP1 and SSP5 are very close, and therefore their line plots are overlapping.

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 scenario driver based on a certain deviation from their reference values. This deviation was set according to the parameter itself and to the extent that avoid extreme model responses in output variables (e.g., a FeliX projection higher than any existing projections by other models). For example, a highly sensitive parameter such as fertility rate had a narrow uncertainty range to make population projections fall within the projections of other IAMs. Supplementary Table 2 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 in the timing of scenario drivers as well to account for the delay in future changes (e.g., the diet change driver can impact a scenario from 2030). This delayed, gradual emergence of changes in scenario drivers was consistent with the implementations of the shared socioeconomic pathways in marker models (van Vuuren *et al.*, 2017).

2.7 Cross-validation

We compared our scenario projections (Section 2.6) across socioeconomic, energy, climate, and land and food sectors with the same SSP-RCP projections by other research organisations (Dellink *et al.*, 2017; Jiang & O'Neill, 2017; Leimbach *et al.*, 2017; Samir & Lutz, 2017), and other 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), to ensure their consistency. This comparison did not aim to reproduce the same patterns to the other models due to differences in model structure and limited quantitative harmonisation of input data across models. Instead, we assessed whether our projections fell within a similar numerical range and whether they can provide a consistent story across different sectors and under different scenarios, aligning with our qualitative scenario assumptions (Section 2.3). Where our projections differed from past projections, we offered explanations for the difference.

3 Results and discussion

3.1 Projecting socioeconomic, energy, climate, and land and food future developments

Figure 4 presents future scenario projections to 2100 in four key sectors (i.e., socioeconomic, energy, land and food, and climate) with 23 control variables, compared against the projections of other integrated assessment models (see methods in Sections 2.6 and 2.7). The selection of these 23 control variables is based on the same scenario outputs reported in the SSP database (IIASA, 2018) for comparability. The quantification of scenarios across sectors with the FeliX model should provide consistent storylines in harmony with the five narratives of the shared socioeconomic pathways (O'Neill *et al.*, 2017) and also in line with scenario input assumptions (Section 2.3, Supplementary Table 1) as we describe below for each scenario.

The SSP1-2.6 projections represent high socioeconomic prosperity where access to all levels of education (as a proportion of population size), especially higher education, increases (Figure 4d) with improvement in gender inequality. Global population peaks around mid-century and declines significantly by 2100 (Figure 4a) due to the assumption of a declining fertility rate. Economic growth also booms due to fast technological progress (Figure 4e). While rapid economic growth would normally increase overall energy use, the assumption of widespread energy-efficient technologies and a transition to low energy intensity services in this scenario (Supplementary Table 1) attenuates the increase in energy demand (Figure 4h). Most of the energy demand is also met through adoption of renewable (especially solar) energy (Figures 4l to 4n) in response to the steep cost reduction of technologies. This transition results from assumptions of high investment and technological progress, high environmental consciousness, and increasing production costs (e.g., carbon price costs) of using fossil energy (Supplementary Table 1). Similar sustainability transitions are also observed in the food and land sector. Environmental consciousness from educational attainment, especially at tertiary levels, along with low population growth, promotes healthy diets with low animal-calorie shares (Figure 4q). This also coincides with land productivity growth and high crop and livestock yield (because of 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, land-based GHG emissions mitigation) create a high potential for mitigation with low-range emissions (Figure 4w) and low radiative forcing levels (Figure 4v) by 2100.

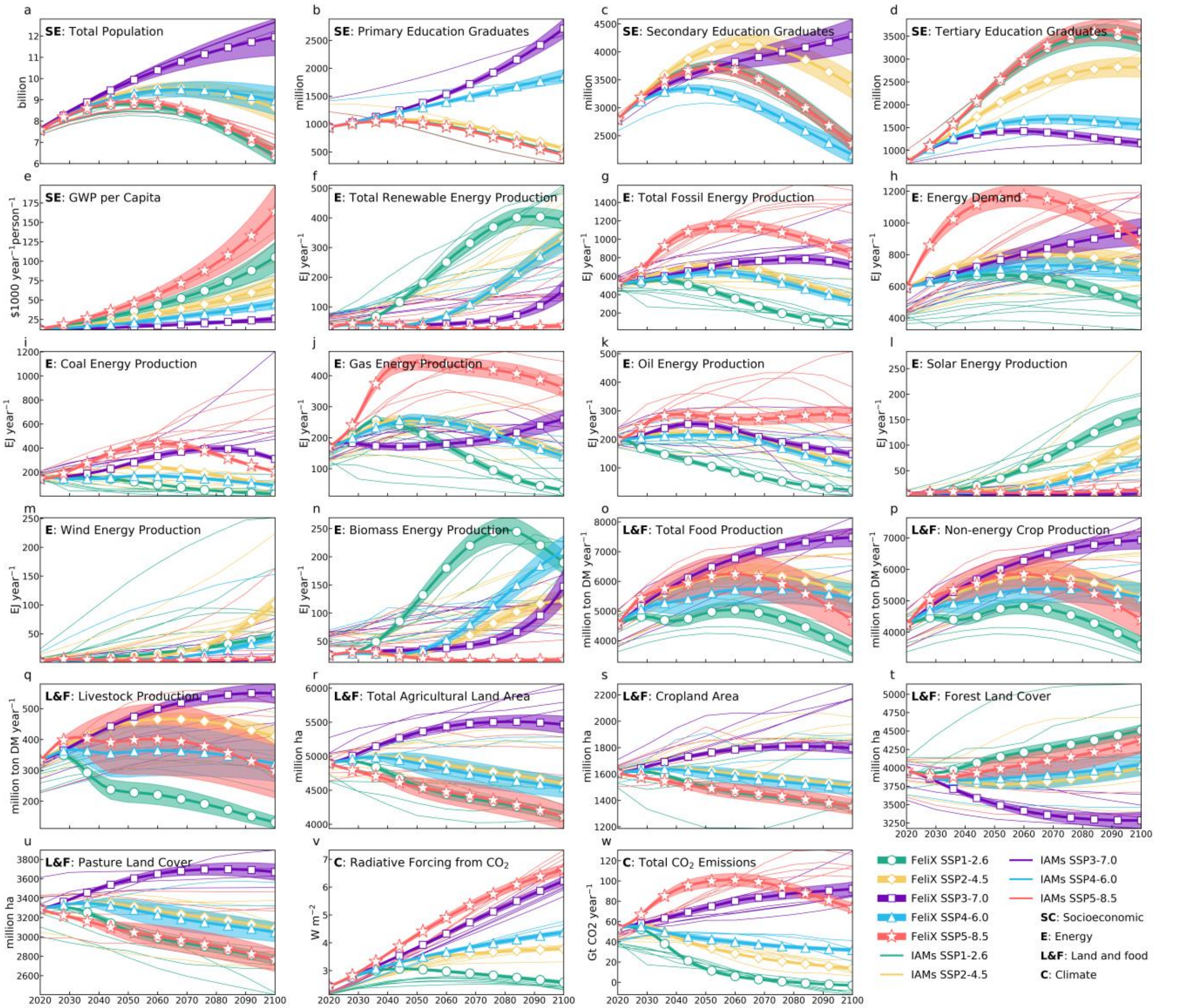

Figure 4. Scenario projections with the FeliX model and their comparison with the projections of major demographic and economic models (Dellink *et al.*, 2017; Samir & Lutz, 2017) and integrated assessment models (Bauer *et al.*, 2017; Calvin *et al.*, 2017; Fujimori *et al.*, 2017; Kriegler *et al.*, 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. See Supplementary Figure 2 for the detailed specification of projections with other IAMs.

The SSP2-4.5 projections follow business-as-usual trajectories with 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 is also a moderate rate of agricultural land expansion and deforestation and a relatively high animal caloric supply (Figures 4o to 4u) due to assumptions on the continuation of current (high meat) diet regimes (Supplementary Table 1). Together, these trajectories result 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 scenario results in the worst socioeconomic projections among all scenarios (Figures 4a to 4e). A very slow economic growth leads to an underdeveloped education system, especially at the tertiary level, which limits the training of a skilled labour force and creates further challenges for economic development. Slow economic progress along with limited educational opportunities induces rapid population growth and declining wellbeing and life expectancy across the population. A relatively weak economy normally has a reduced demand for energy. However, assumptions around low environmental standards and poorly performing public infrastructure in this scenario (Supplementary Table 1) increases energy demand compared to the business-as-usual trajectories (Figure 4h). Transition to renewable (i.e., wind and solar) energy is slower than the business-as-usual (Figures 4l to 4n) due to 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 necessitate 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 result 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 show 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 have relatively similar low and high trends (respectively) compared to business-as-usual. These socioeconomic, energy, and food and land trajectories together result 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 projections show 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 is not sustainable and results in high, resource-intensive consumption, with severe impacts for energy and climate. Rapid economic growth promotes a lifestyle with the highest energy demand among all scenarios (Figure 4h). However, contrary to SSP1-2.6, this high energy demand is 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 remains 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 results 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, result in the highest emissions and radiative forcing among all scenarios, creating significant challenges to mitigation (Figures 4v and 4w).

The adoption of different marker and non-maker IAMs was useful in providing insights into the uncertainties related to model structure and/or the interpretation/quantification of the qualitative narratives in the model. While the scenario projection of marker IAMs in Figure 4 can be interpreted as being representative of a specific SSP-RCP development, they are not considered as a central or median interpretation. This means that for each SSP-RCP combination, numerous alternative outcomes are possible—and they are equally valid—as long as they are internally consistent and harmonious with their narrative descriptions. The projection of scenarios with the (non-marker)

FeliX model presented some of these alternative yet equally valid outcomes. Despite the parametrisation uncertainty and variation driven by differing model structure and implementation of qualitative narratives, the FeliX scenario projections are generally aligned with those of other marker IAMs across all sectors for most control variables (Figure 4). However, as would be expected, there are a few exceptions.

First, the FeliX projection of coal production in SSP5-8.5 is lower than projections from other marker IAMs from 2070 onwards (Figure 4i). 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 the initial parametrisation) makes coal less cost competitive compared to other fossil (i.e., gas, oil) as well as renewable (i.e., solar, wind) sources due to assumptions about the declining cost of production from other energy sources over time. This propagates a more rapid decline in coal production consistently across all scenarios (including in SSP5-8.5) in the FeliX model. The conservative assumptions on renewable costs in the global climate (IPCC) scenarios (and hence less competition that can reduce fossil energy production) have also been discussed in the literature. Similar variations, resulting from differing model structural design and assumptions, 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 have the highest solar and MESSAGE-GOLOBIOM has 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 remains much higher than renewable energy production in the same scenario and is also higher than coal production in other FeliX SSP-RCP projections. This keeps SSP5-8.5 consistent with the 'fossil-fuelled development' storyline in the original SSP narratives (O'Neill *et al.*, 2017).

Second, variation in projections between FeliX and other models in food and land variables (most notably in SSP1-2.6 and SSP3-7.0) can be explained by FeliX's additional diet change module (Eker *et al.*, 2019). 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 is modelled mainly through the diet change module which formalises 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. 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 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 (due to the diet change module) in FeliX (as explained above) has resulted in slightly lower projections of CO_2 emissions, most notably in SSP5-8.5, compared to the other models. Similar variations across all sectors were also observed between the projections of marker and non-marker integrated assessment models, driven by the diversity of model structures and their initial parameterisation (Popp *et al.*, 2017). Therefore, with different plausible assumptions in the energy and food sector, FeliX projections respond to the calls for exploring a wider uncertainty space.

3.2 Exploring SDG indicator trajectories

The performance against SDG indicators varies substantially across different scenarios and indicators over time (Figure 5). Among the analysed scenarios, the accumulation of changes in SSP1-2.6 between 2050 and 2100 can create promising long-term trajectories. However, this is not the case in other scenarios, driven by complex 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.

Gross World Product (GWP) per capita (Figure 5e-i), adolescent fertility rate (Figure 5b-ii), and mean years of schooling (Figure 5c-i) are the three socioeconomic indicators with the fastest improvement over the century in SSP5-8.5 and SSP1-2.6 (across SOWs) by 2030 and beyond. This is due to 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 create 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 can lead to improving trajectories towards 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 can achieve 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). As we discussed in Section 3.1, the SSP1-2.6 scenario can also result 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 is 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 outperforms 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).

By contrast, socioeconomic prosperity in SSP5-8.5 results 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 translates 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 imposes a severe risk for achieving the IPCC climate targets (Rogelj *et al.*, 2019). The SSP5-8.5 scenario also results in a high land-based animal calorie supply of 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 also leads 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 (Section 2.3), can enable the achievement of high food demand and production with less agricultural land (Figure 4r). This results in improving trajectories in indicators related to forest land (Figure 5h-i) throughout the 21st century.

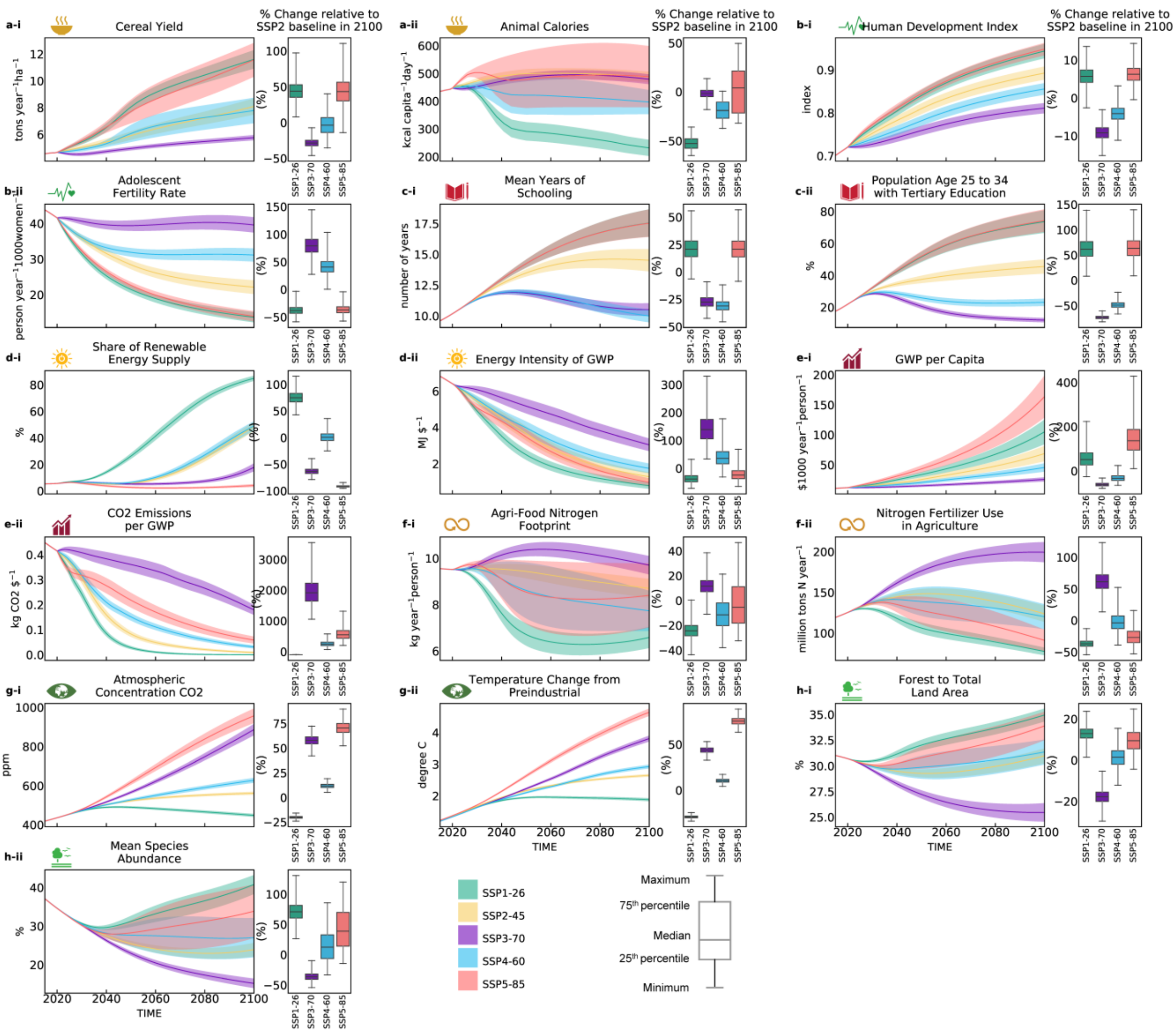

Figure 5. SDG-scenario evaluation across 50,000 SOWs. In each subplot, the envelope plots show each indicator's trajectory across five scenarios with descriptive statistics (mean and standard deviation) to represent the average projected value and the uncertainty range of each indicator's projection. 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).

Far less improvement occurs in SSP3-7.0 and SSP4-6.0 across all indicators and SOWs. The global trajectories under these two scenarios are deteriorating in most of socioeconomic, energy, climate, and biodiversity indicators. This results 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 Section 3.1. For instance, trends over the century reach 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 results 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 can be attributed to 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 increases strongly (Figure 4r), resulting in further demand for fertiliser application and greater deforestation and biodiversity loss.

4 Conclusions and future work

Future socioeconomic and environmental change, often characterised by abrupt shocks and surprises, can challenge the achievement of the sustainable development goals and create uncertainty around progress to sustainability by 2030 and beyond. Interacting systems with multisectoral dynamics occurring at an unprecedented pace can also create a further complexity in understanding the impacts of future global change on sustainable development. We argue that this combination of uncertainty and complexity requires scenario modelling with integrated and exploratory approaches that can connect social and biophysical dimensions of the Earth system and simulate their interactions under many possible future.

To address this need, we used the shared socioeconomic pathways and representative concentration pathways frameworks in the SDG context as benchmarks for scenario modelling. Our adoption and quantification of these scenarios, using a new integrated assessment model of different type (i.e., a system dynamics model) and different structure (i.e., feedback-rich) also enabled a scenario uncertainty exploration of the reference projections with the marker integrated assessment models. To adopt and implement these scenarios, we proposed a methodology and articulated its technical details, with examples from the implementation of the five combinations of the shared socioeconomic pathways and the representative concentration pathways. We projected future scenarios and their various realisations under uncertainty in population, economy, energy, land, food, and climate systems from 2020 to 2100, compared our projections with those of other integrated assessment models, and assessed the trajectories of 16 SDG indicators across eight goals by 2030 and beyond.

Our study contributed to sustainability science by enabling a wider adoption of the shared socioeconomic pathways and the representative concentration pathways to explore their broader implications beyond the original foci of climate change and on new SDG-related indicators. The methodology also expanded the limits of benchmark scenarios by exploring model structural uncertainty and the uncertainty of quantifying the narratives of global scenarios and generating a wider diversity of possible future realisations using deep uncertainty and exploratory modelling methods (Marchau *et al.*, 2019).

While our proposed methodology enabled the parameterisation of global scenarios to evaluate SDG trajectories, it did not measure the actual progress towards *explicit targets* nor discover the critical areas of the uncertainty space responsible for the system's tipping points and instabilities in achieving these targets. An important next step in the further development of our methodology is to set explicit targets on the SDG indicators to be used as thresholds for quantifying the progress towards the SDGs and measuring the chance of success or failure by 2030 or beyond. Another future work is to incorporate scenario post-processing techniques, such as scenario discovery (Hadjimichael *et al.*, 2020; McPhail *et al.*, 2020) and robustness analysis (Gold *et al.*, 2019; Herman *et al.*, 2020) from exploratory modelling, to identify tipping points where efforts may fail to achieve targets. The identification of tipping points as warning signs can inform proactive and anticipatory responses to external shocks and help decision-makers keep human and environmental systems on-track for achieving sustainability targets.

Enhancing the robustness of insights obtained about the SDGs requires the expansion of scenario space and its uncertainty exploration. However, this comes at the expense of increasing the computational costs of simulations and often leads to limiting the assessment to a set of most plausible scenarios. Our model-based assessment of the SDGs was no exception. Our results and their interpretations were within the assumptions of five specific scenarios aligned with five widely-adopted SSP-RCP combinations (O'Neill *et al.*, 2020). However, there are other potential combinations of scenarios that we did not investigate in the current study. 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 ideal for IPCC mitigation pathways compatible with 1.5 degree °C (Rogelj *et al.*, 2018b). Future research should 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 reduction of fossil energy supply and emissions) compared to our results. The further improvement (e.g., <1.5 degree °C global temperature change) in the climate impacts of SSP1 could be possible via a greater reliance on atmospheric CO_2 removal technologies and practices (Smith *et al.*, 2016). However, this level of CO_2 removal has not been demonstrated at this scale 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 works on integrated assessment and scenario modelling, therefore, require capturing the societal dynamics of lower scales beyond the currently dominant uniform assumptions and aggregation of data and to better connect them with global biophysical and policy-making processes (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.

Acknowledgments

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Code and Data Availability

The datasets/code generated during this study are available for peer review purposes from: https://github.com/enayatmoallemi/Scenario_Modelling. The datasets/code will be deposited permanently on Zenodo (with the link, DOI, and data citation) if the article is eventually accepted. 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. Key scenario parameters and their quantification in the FeliX model.

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