Supporting Materials for

Diversifying models for analysing global change scenarios and sustainability pathways

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

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

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

[3]Nijmegen School of Management, Radboud University, The Netherlands.

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

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

[†] These authors contributed equality.

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Supplementary Methods

Model description

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

Model sensitivity analysis

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

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

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

Model calibration

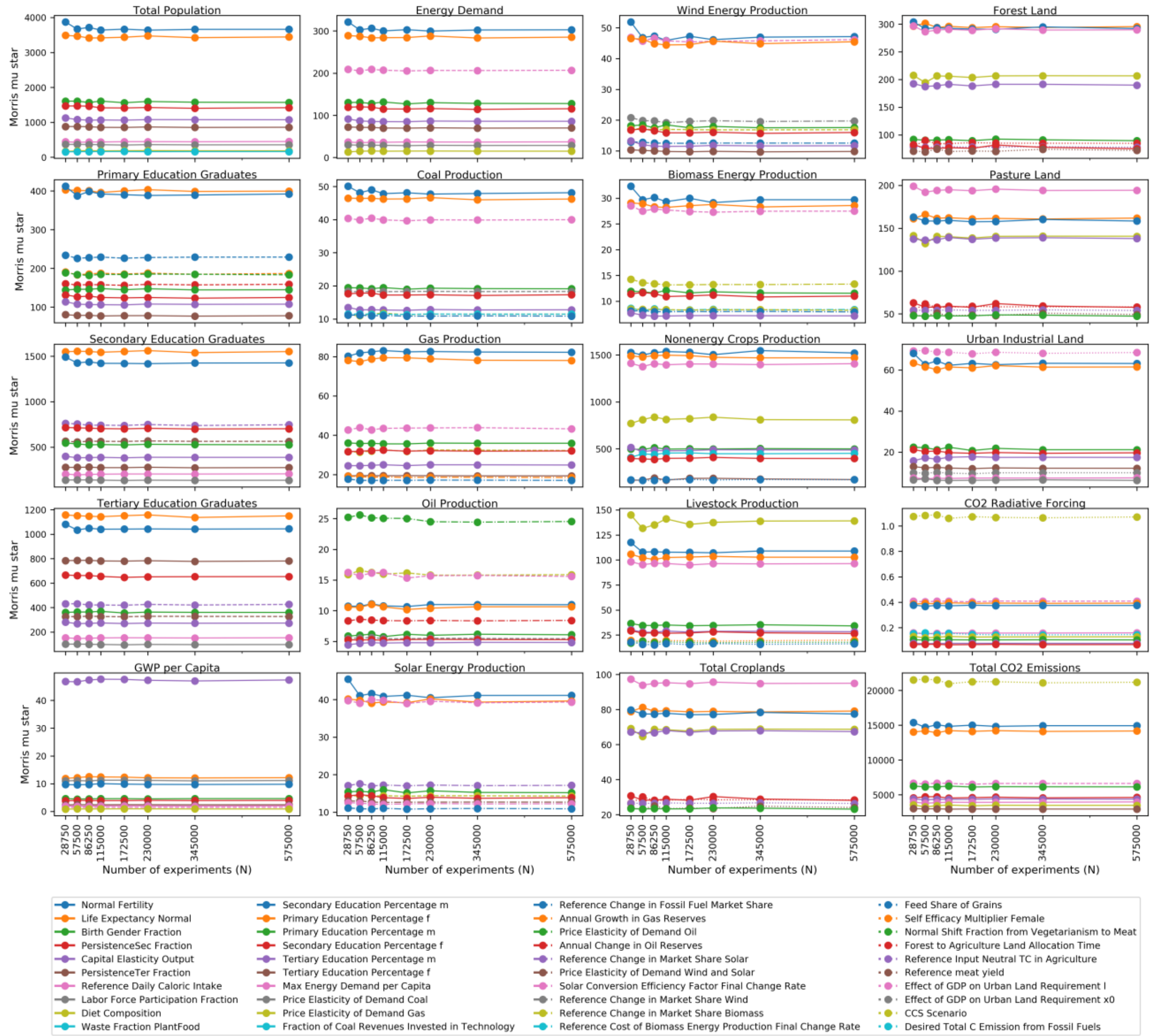
Among various influential parameters, those related to the demographic and macro-economic input assumptions were the only ones harmonised with other integrated assessment models as they form the fundamental underlying logic for each SSP, and their harmonisation is important for generating internally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

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

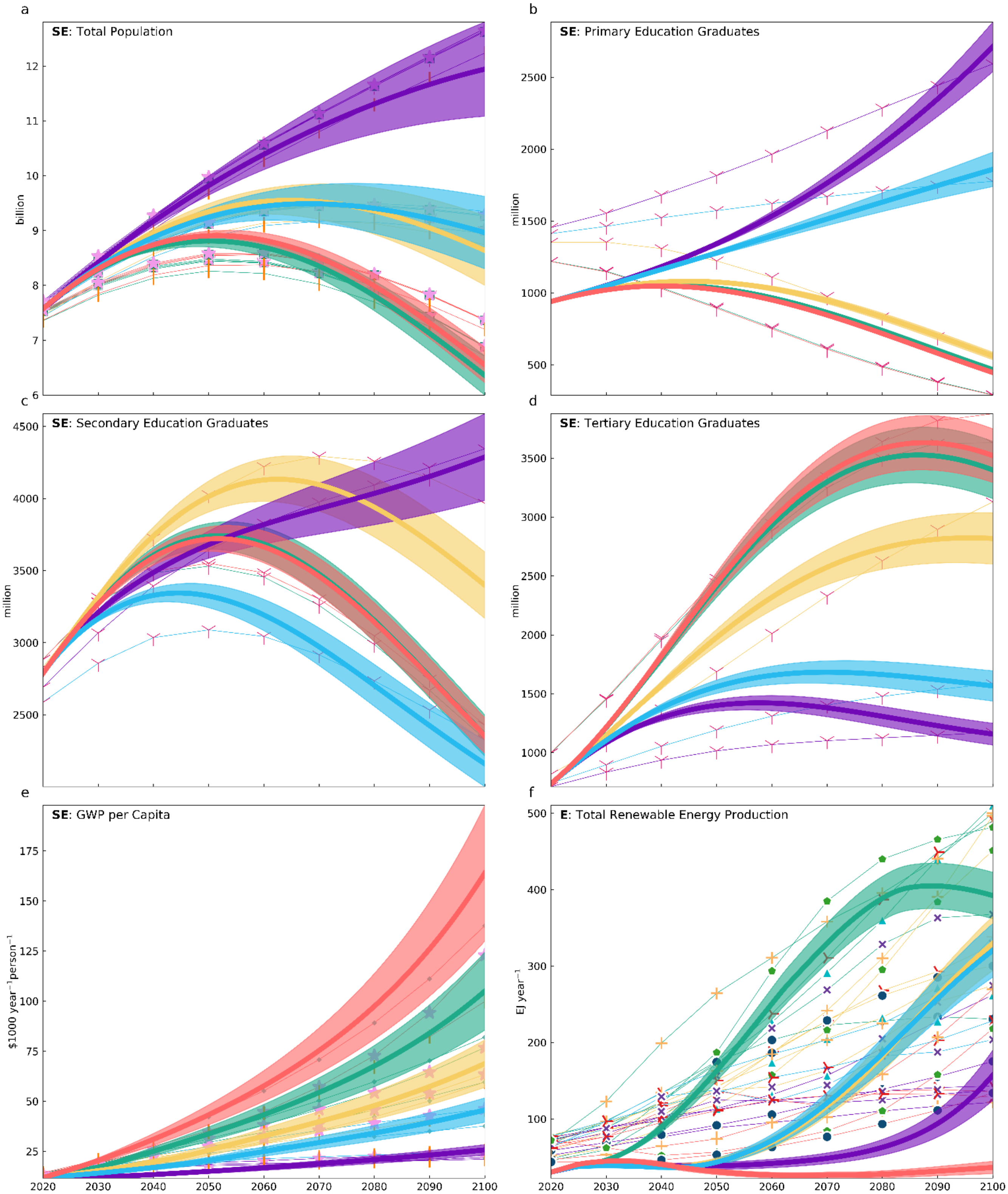
Design of experiments

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

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

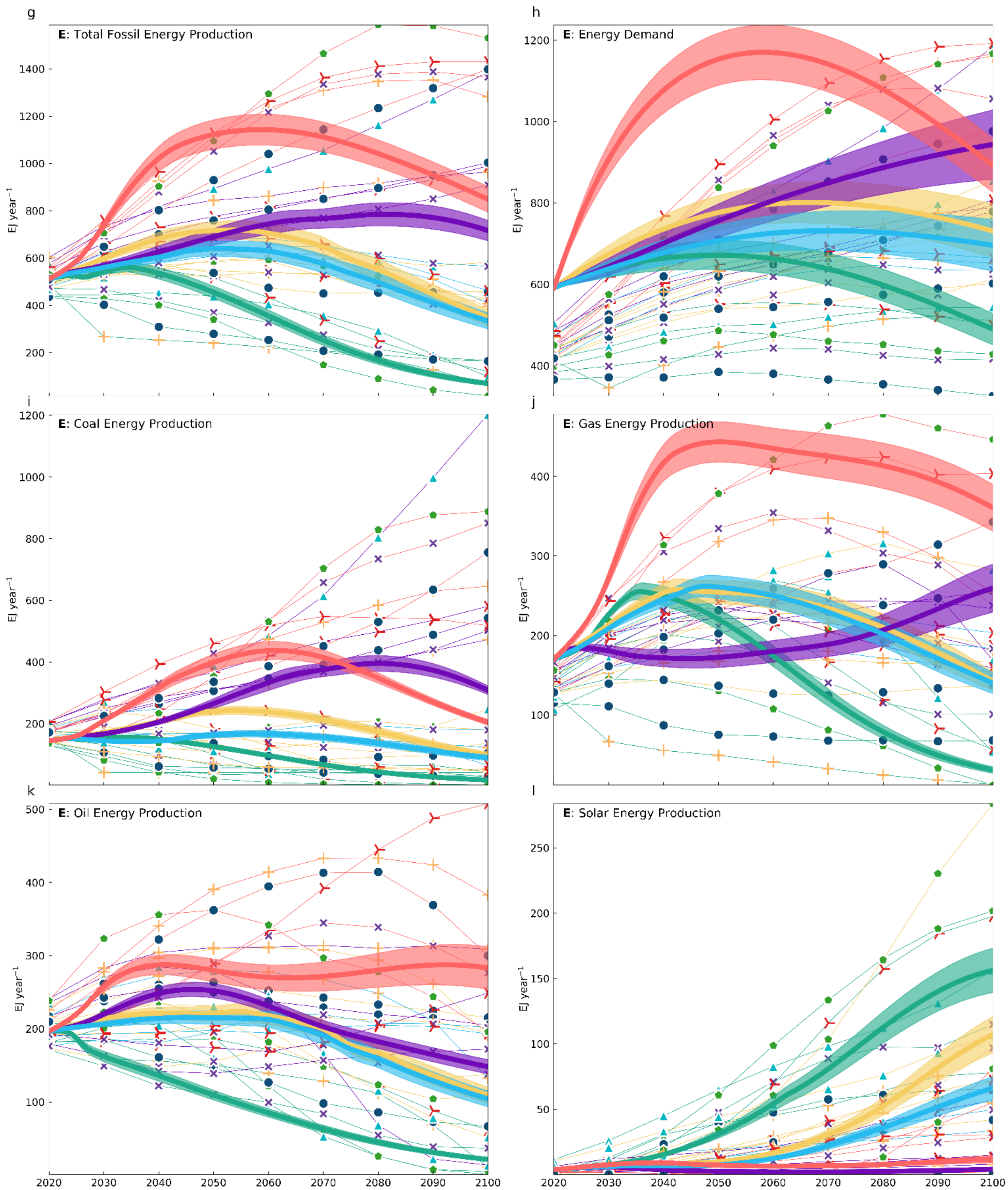


Supplementary Figure 1. The convergence of parameter ranking and sensitivity index in the projection of model's control variables in year 2100, for the increasing number of sample size. The figure only shows the convergence of top 10 most sensitive parameters which for better visibility.



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

Continued.


g
E: Total Fossil Energy Production
h
E: Energy Demand
i
E: Coal Energy Production
j
E: Gas Energy Production
k
E: Oil Energy Production
l
E: Solar Energy Production
EJ year^{-1}
2020
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2100

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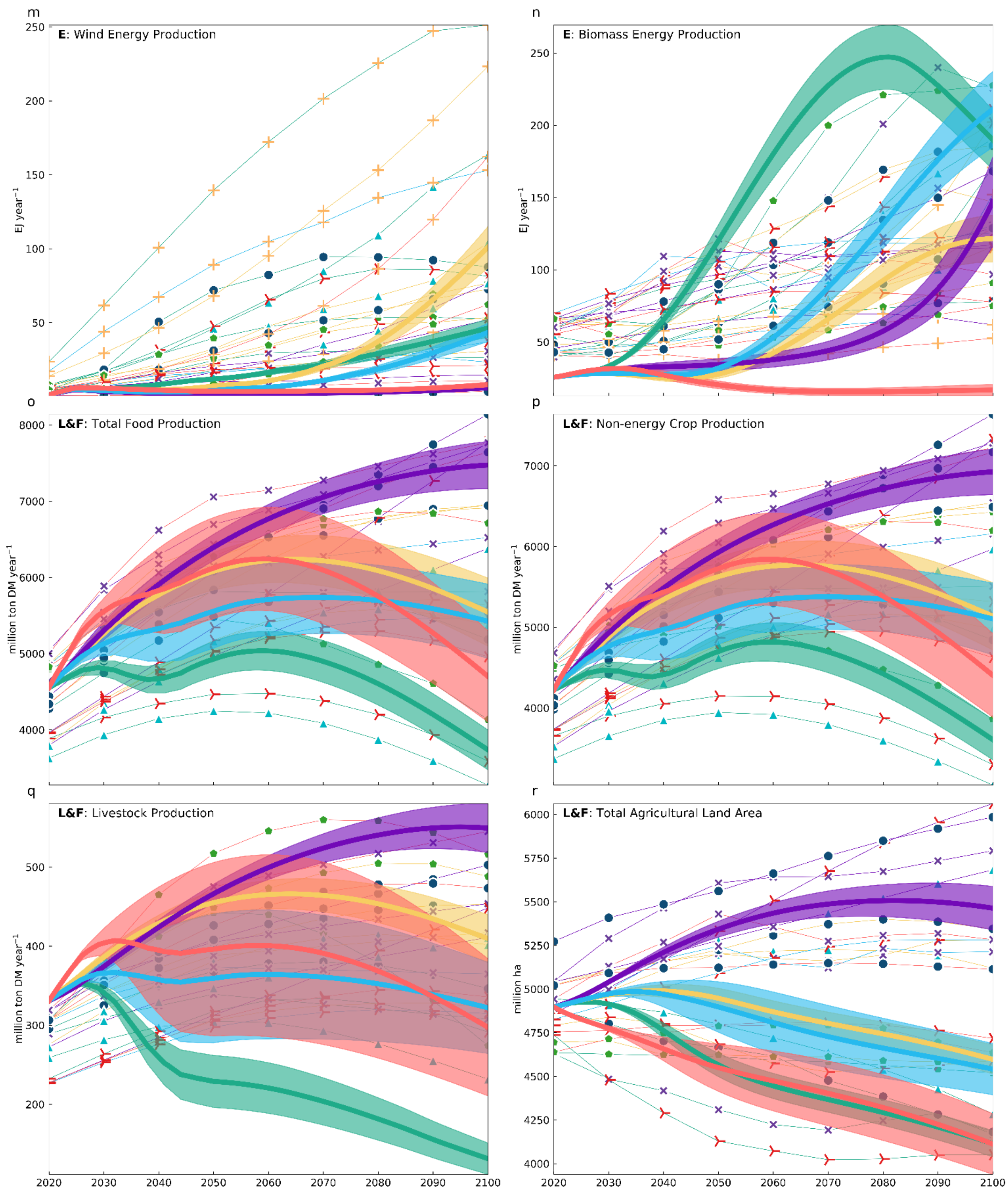
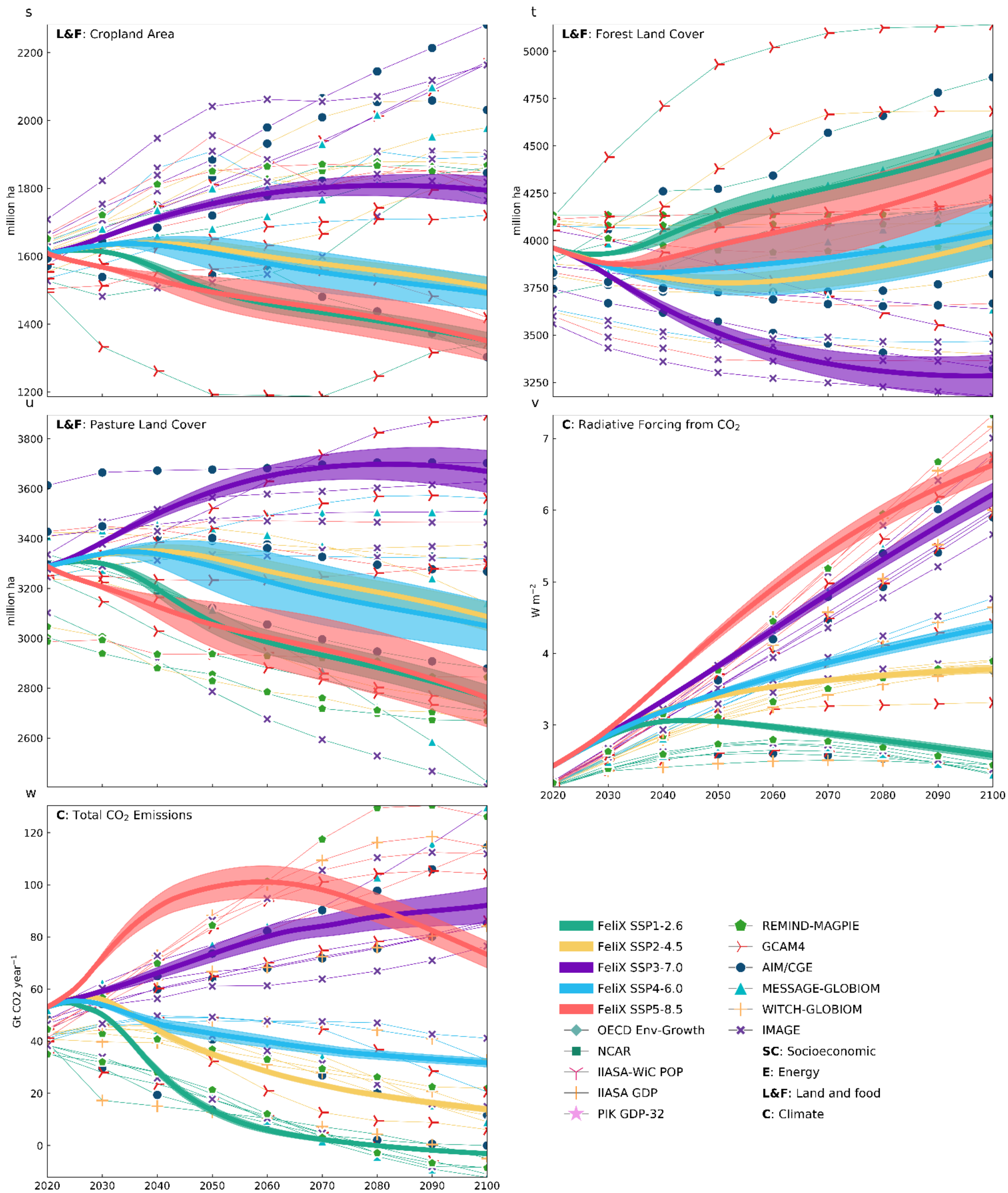

m
E: Wind Energy Production
EJ year⁻¹
n
E: Biomass Energy Production
EJ year⁻¹
o
L&F: Total Food Production
million ton DM year⁻¹
p
L&F: Non-energy Crop Production
million ton DM year⁻¹
q
L&F: Livestock Production
million ton DM year⁻¹
r
L&F: Total Agricultural Land Area
million ha
2020 2030 2040 2050 2060 2070 2080 2090 2100

Continued.



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

Supplementary Table 1. Qualitative assumptions of scenarios

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

Continued.

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

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

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

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