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Coupled social-land dynamics and the future of sustainable consumption

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Abstract

Dietary patterns have long been a driver of global land use. Increasingly, they also respond to it, in part because of social forces that support adoption of sustainable diets. Here we develop a coupled social-land use dynamics model parameterised for 164 countries. We project global land use under 20 scenarios for future population, income, and agricultural yield. When future yields are low and/or population size is high, coupled social-land feedbacks can reduce the peak global land use by up to 2 billion hectares, if socio-economic barriers to adopting a sustainable diet are sufficiently low. In contrast, when population growth is low or yield is high, reductions in income elasticity can increase peak land use by 100 million hectares. The model also exhibits a regime of synergistic effects whereby simultaneous changes to multiple social and economic parameters are required to change land use projections. This research demonstrates the value of including coupled social-land feedbacks in land use projections.

Main

From 1961 to 2013 global food demand went up threefold, from 6.4 trillion to 19.4 trillion kilocalories (kcal) per day. This massive increase is attributed to an increase in the world population from 3 to 7.1 billion and an increase in average per capita consumption of food from 1800 kcal/day to 2600 kcal/day over this period [1]. Land is the primary global food supply. In 2013, an estimated land equivalent of 3.5 billion hectares was consumed (72% of agricultural land in that year) while approximately 1.4 billion hectares of land was spent on food wastage [2]. Future expansion in global agricultural land and/or increased intensity of existing farmland usage is therefore a highly probable pathway to meet the enhanced demands of the 21st century. However, agricultural expansion and intensification represent major ecological threats, ranging from clearing of forests and habitat fragmentation [3, 4] to increased greenhouse gas emissions [5, 6].

Agricultural intensification faces an uncertain future. From 1961 to 2013, production gains were mostly due to the steady growth in land productivity [5, 1]. Some studies suggest that certain major crops are approaching their yield ceilings in rich countries [7, 8, 9]. There has been a deceleration in yield growth across the globe primarily due to decreasing investment in agricultural research and reduced food production prices in both higher and lower income countries [10]. Slowing intensification may trigger agricultural land expansion to catch up with rapidly growing demand for food.

Mathematical models of sustainable food systems are becoming an increasing topic of research [11, 12, 13, 14, 15, 16, 17]. Research on sustainable pathways for agricultural technologies tend to

39 focus on the supply side of the problem. On the demand side, models often stipulate future demand
40 trajectories that are independent of how the model variables evolve. For instance, sophisticated land
41 system ensemble models that are used to project land use in Intergovernmental Panel on Climate
42 Change (IPCC) reports since their models use scenarios for homogenized dietary consumption
43 patterns as inputs and, as such do not study the dynamics of system-induced drivers of human
44 consumption behaviours [18, 19, 20, 21]. The importance of incentivizing sustainable consumption
45 has been noted [22]. Dietary patterns can heavily influence trajectories of global land use [20, 23,
46 24, 25, 26] and individuals include environmental factors while making dietary decisions [27, 28]
47 and therefore land use dynamics and socially-influenced dietary choices are coupled to one another
48 through two-way feedback. However, there has been limited investigation into understanding how
49 these shifts in dietary patterns evolve within populations due to social and economic factors, and
50 in particular how they respond to changing land use.

51 Sustainable consumption is an economically and socially induced process that evolves endoge-
52 nously in a population and hence can benefit from systematic study using theoretical models. From
53 the individual perspective, adopting a land-sparing sustainable diet may involve paying a cost of
54 losing the personal satisfaction of consuming meat [29, 30]. However, everyone benefits from an
55 individual’s choice to adopt a sustainable diet, since scarce global land use is reduced as a result of
56 that choice. Hence dietary choices represent a public goods game, where individuals may choose to
57 contribute to a common benefit that all members of the group receive, even if they did not make
58 a contribution [31, 32]. Modeling social behavior in public goods games often uses models of social
59 learning dynamics from evolutionary game theory, which captures how individuals learn behaviours
60 from one another [33, 34, 35]. Interest has grown in coupling dynamic social learning models to
61 models of natural processes such as the global climate system [36, 37] and terrestrial ecosystems
62 [38] although social learning dynamic models have not been applied to study coupled dynamics of
63 global land use and dietary decision-making in human populations, to our knowledge.

64 Here, we introduce a social learning modelling framework for coupling the country-level dynam-
65 ics of sustainable dietary decision-making under social learning dynamics to country-level land use
66 dynamics. Our objectives are to: (1) show how models of social dynamics and land use dynamics
67 can be coupled to generate novel predictions that are not possible using approaches that treat these
68 systems in isolation from one another, and (2) gain insight into how potential coupled social-land
69 use processes alter both projected global land use and projected dietary trends. Our objective was
70 not to generate projections for policy use. Hence, we opted for a minimal model that was easier to
71 fit to data and gain insight from.

72 Model Overview

73 Our mathematical model describes a social learning process by which individuals learn dietary
74 behaviour from others. Our model captures the two-way feedback between land use and dietary
75 practice: as dietary practices impact global land use, the resulting trends in global land use can, in
76 turn, stimulate behaviour toward more sustainable diets in a closed feedback loop, albeit modified
77 by socio-economic drivers. Details of the model appear in Methods.

78 For every country, i , we define bounds for maximum and minimum per capita land use in
79 year t ($c_i^{U,max}(t)$ and $c_i^S(t)$ respectively). We classify individuals as having either sustainable or
80 unsustainable diets. Individuals with a sustainable diet consume $c_i^S(t)$ hectares per capita in year
81 t . Those with unsustainable diets increase their consumption based on per capita income up to a
82 maximum $c_i^{U,max}(t)$. We define h_i as the elasticity of food consumption with respect to income in
83 country i (or just, income elasticity of food consumption in i). The higher h is, the more rapidly

84 consumption changes with income for those practicing an unsustainable diet (see Methods). The
85 estimate procedure for $c^{U,max}$ and c^S appears in Methods. Beyond 2013 (the last available year
86 in the FAO food balance sheets), these bounds are extrapolated under different scenarios defined
87 by a parameter f (a number between 0 and 1). Low values of f represent scenarios where future
88 global yields are higher. High values of f represent inferior (low) yield futures (see Methods for a
89 mathematical representation of the scenarios).

90 We assume every country i is characterized by a barrier to adopting a sustainable diet, σ_i , such
91 that when global land use $L < \sigma_i$, the perceived costs of a sustainable diet push the population
92 toward an unsustainable diet, while when $L > \sigma_i$, the population moves toward the sustainable
93 diet. σ_i represents a barrier to achieving population-wide adoption of a sustainable diet due to the
94 combined effects of various psychological, social and economic factors. The rate of dietary change is
95 dictated by κ_i , which describes how fast social learning occurs in country i . κ_i is a control knob that
96 determines how often an individual samples other individuals in the population regarding their
97 diet. If an individual on a non-sustainable diet samples an individual on a sustainable diet and if
98 $L > \sigma_i$, they switch to a sustainable diet with a probability proportional to the difference $L - \sigma_i$. A
99 similar process occurs for the switch from sustainable to unsustainable diets (see Methods). When
100 $L > \sigma_i$, the proportion x of individuals on a sustainable diet increases as individuals switch from
101 an unsustainable diet to a sustainable diet. The opposite happens in the unsustainable regime. A
102 high value of κ_i can accelerate change in either direction depending on the difference between L
103 and σ_i .

104 We use a previously published model [2] to generate country-level land use data based on
105 dietary patterns from 1961 to 2013. We fit our model to these data to estimate κ_i , σ_i and h_i for
106 166 currently existing countries (see Appendix SI Section 1 for methods of parameter estimation
107 and Appendix SI Section 4 for countries included). These estimated parameters were taken as our
108 baseline parameter values. Under the umbrella term ‘agricultural land use’ we included land used
109 for agriculture, pasture and feed generation. Our land calculations excluded land equivalent of
110 food wastage: we accounted only for the land that is used to generate the food that ends up being
111 consumed by the population (See Methods for details). The model parameters, κ , h and f , are real
112 numbers in the interval $(0, 1)$.

113 Results

114 We make global land use projections for 20 scenario combinations for the 164 countries we analyzed
115 (see Appendix SI Section 4 for details on countries used). For country-level population and income
116 projections, we use the five shared socio-economic pathway (SSP) scenario markers, SSP1 to SSP5
117 [39, 40]. Each SSP scenario represents a unique storyline for the future that dictates the trajectory
118 of population and income in countries (among other things). Although these scenarios have unique
119 storylines for yield growth, we also show results for different possible future yield trajectories
120 under each SSP scenario. SSP1 is characterized by relatively high income and small population.
121 In SSP2, current trends of population and income continue, and moderate progress is made by
122 achieving income convergence between countries. SSP3—also called the road to regional rivalry—is
123 characterized by an overall high population growth and low income levels in developing countries.
124 The SSP4 future sees high disparity in economic growth rates between high income and low income
125 countries; global growth is less rapid compared to SSP1. In a SSP5 world, economic development is
126 of utmost priority, income growth is high, on average, and it is coupled with strong improvement in
127 education that leads to reduced fertility and hence a relatively small but well-educated population.
128 See Appendix SI Figure 11 for population and income projections under the five SSP scenarios until

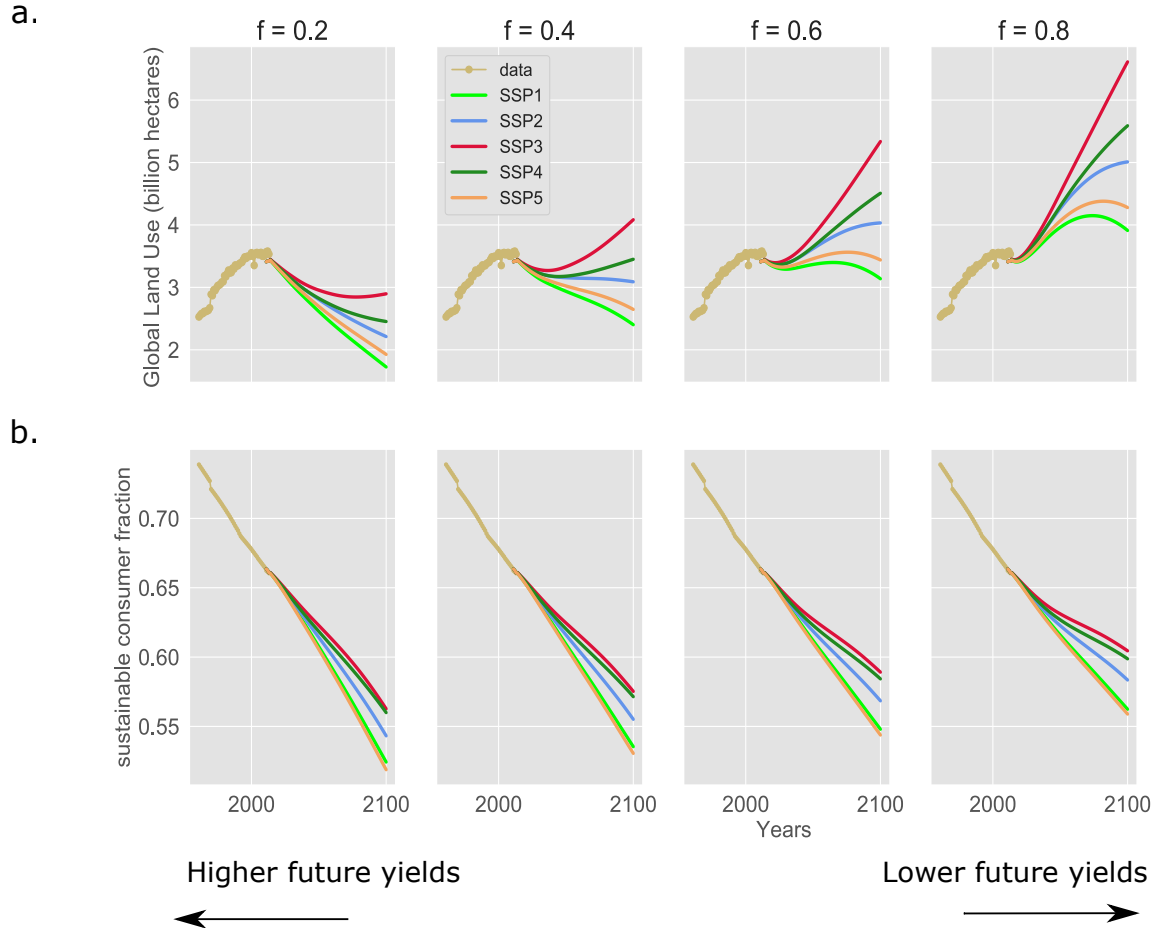


Figure 1: **Global land use projections to 2100 under multiple yield and SSP scenarios**
(a) Global agricultural land use projections till 2100 (excluding land equivalent of food waste) under 20 scenario combinations. The four columns cover the yield scenarios of $f = 0.2, 0.4, 0.6$ and 0.8 . Yellow dots show the time series data for land use from 1961 to 2013. Data from 1961 to 2013 is generated using Ref. [2]. Projections in solid lines begin from 2011 and continue till 2100. **(b)** Model projections of fraction of global population consuming sustainably. See Methods for model definition of sustainable consumption. Yellow dots show time series data for fraction of people consuming sustainably between 1961 and 2013 estimated as in Ref. [2].

129 2100. For each of the five SSP scenarios, we also explored four scenarios for future agricultural
 130 yield: $f = 0.2, 0.4, 0.6, 0.8$, producing a total of 20 scenarios.

131 **Dynamic social-land feedbacks can partially counteract policy**

132 At the global level, the model shows how social dynamics partially counteract land use impacts
 133 caused by other trends such as changing per capita income and population size. The model predicts
 134 a net decrease in the proportion of individuals practicing a sustainable diet (x , or, ‘sustainable
 135 consumers’ hereafter) from 2013 to 2100 in all scenarios, on account of a high average barrier to
 136 adopting a sustainable diet (σ_i) and increasing per capita incomes (Figure 1b, and see Appendix SI

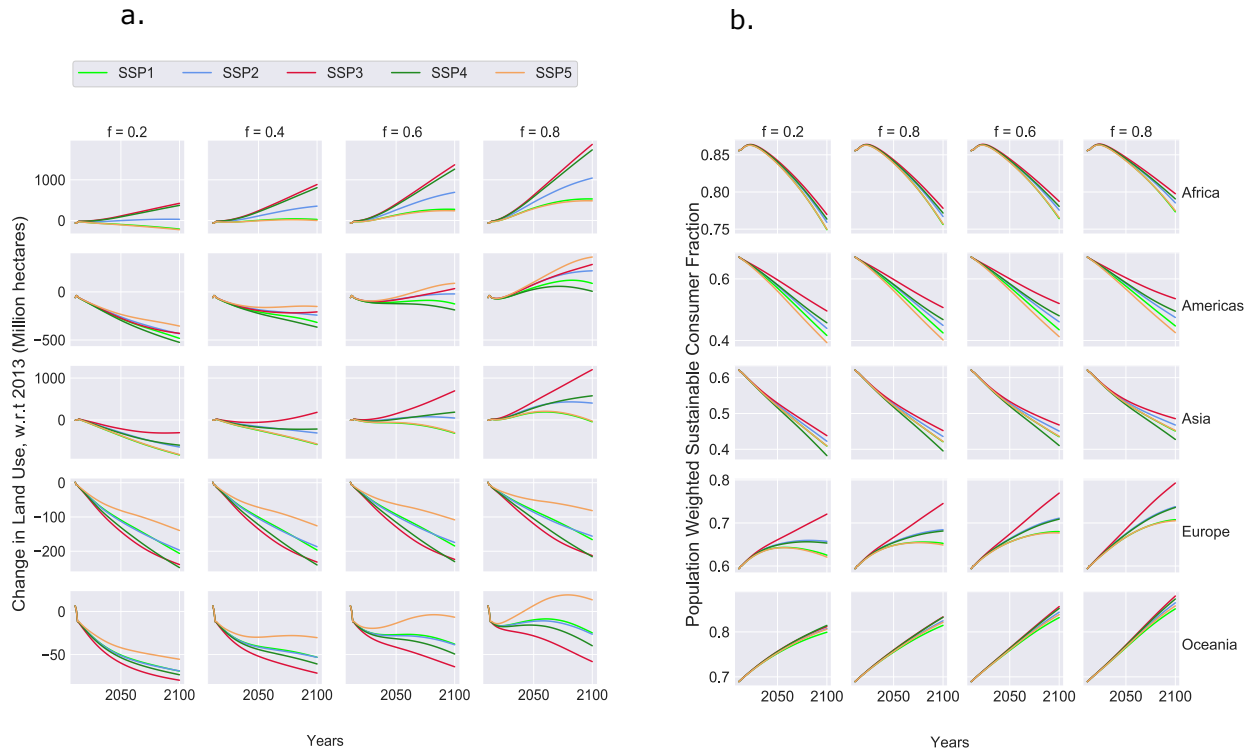


Figure 2: **Global land use projections to 2100, broken down continent-wise, reveal heterogeneity under sustainable behaviour in baseline conditions.** (a) Projections of change in agricultural land use with respect to 2013 (excluding land equivalent of food waste) broken down continent-wise into five major regions - Africa, Asia, Americas, Europe and Oceania (see Supplementary Section 5.2 for division methodology). Projections are shown for 20 scenario combinations (combinations of 5 SSP scenarios and 4 f scenarios). (b) Model projections for fraction of regional population consuming sustainably for 20 scenario combinations. See Methods and Supplementary for formal definitions of sustainable consumption. Only Europe and Oceania show a rise in sustainable consumers over the projecting period (2011 - 2100).

137 Figure 6 for global distribution of baseline σ values). A more rapid decline occurs under SSP5 and
 138 SSP1, on account of lower population sizes and thus lower land use in those scenarios creating a
 139 reduced perception of need to switch to a sustainable diet (Figure 1a). There are more sustainable
 140 consumers higher under SSP3, on account of higher land use in that scenario. In SSP3, due to
 141 reduced global income, unsustainable practitioners cannot consume as much as they could have
 142 with a higher income. However, this does not help reduce global land use because population
 143 size grows fastest under this scenario. Unsustainable practitioners therefore switch to sustainable
 144 diets faster because growing global land use exceeds the barrier to adopting a sustainable diet.
 145 Their behavioural change is, however, of little avail. Since their unsustainable consumption is not
 146 substantially higher than the sustainable level (due to reduced income in SSP3), the effects of this
 147 behavioural change are outweighed by high population growth. On the contrary, in SSP1 and SSP5,
 148 higher incomes allow higher consumption for the unsustainable practitioners. But low population
 149 growth prevents higher per capita consumption from causing a large rise in global land use. As a
 150 result, the temporal evolution to sustainable diets is slower in these scenarios.

151 Under scenarios of higher future yield ($f = 0.2$ and $f = 0.4$), global land use declines from its

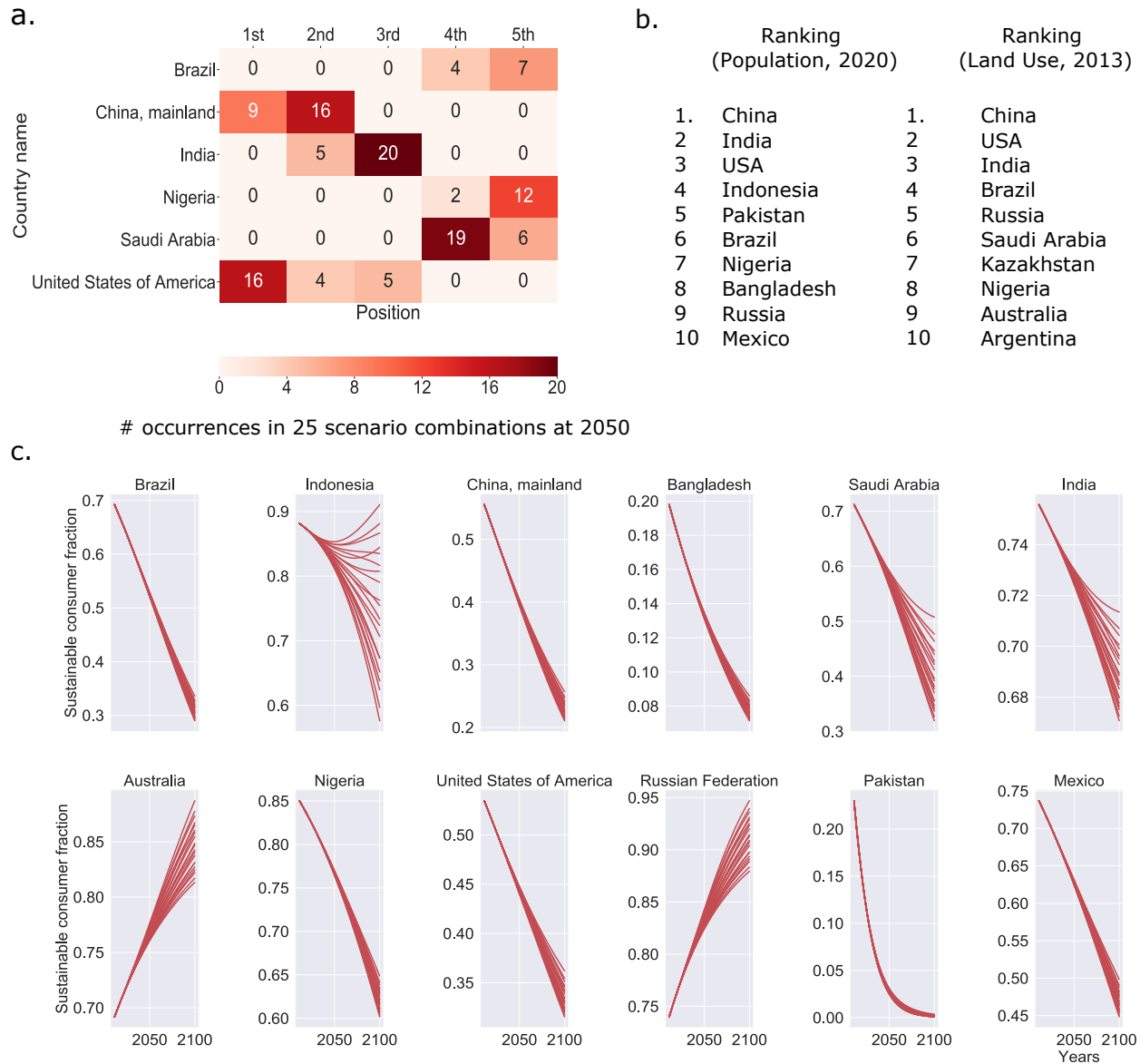


Figure 3: **Countries with high population and high land use show general trend of reducing sustainable behaviour under baseline parameters.** (a) Ranking of countries based on their total land use across 25 scenarios at 2050. Six countries land at least once inside the top 5 positions in 25 scenario combinations (combinations of 5 SSP scenarios and five yield scenarios: $f = 0.2, 0.4, 0.6, 0.8$ and 1). The heat map indicates the number of appearance of a country at a particular ranking position. China and the USA dominate the first two spots while India, Saudi Arabia and Nigeria dominate third, fourth and fifth positions respectively. (b) Table showing ranking of countries based on their population (2020, data) and land use (2013, data generated from model in Ref. [2]). (c) Model outputs of sustainable consumers for the twelve countries that occupy spots in either of the rankings in b.

152 2013 values across most SSPs. The only exception is SSP3 where land use starts to increase again
 153 after a period of decline. This occurs because the global population continues growing throughout
 154 the 21st century under SSP3. Eventually, the effect of population size outweighs the effect of

155 saturating gains in yield. Under scenarios of lower future yield ($f = 0.6, 0.8$), future land use
156 deviates significantly across the SSPs but generally tends upward. We project land use to go as
157 high as 6 billion hectares in the most extreme scenario ($f = 0.8$, SSP3). SSP scenarios with large
158 initial population growth rate (SSP3 and SSP4) do not reach peak land use by 2100. On account
159 of rapidly expanding land use, the sustainable consumers decline less rapidly than in the higher
160 future yield scenarios, but the overall trend is still downward.

161 Taken together, these results show how changes in parameters such as population size and per
162 capita income can cause a social response that partially counteracts those changes. For instance,
163 SSP5, despite being the most sustainable scenario in other respects, does not exhibit the strongest
164 transition to sustainable diets because the reduced population size in that scenario causes a reduc-
165 tion in land use required, and thus reduces the perceived need to transition to a sustainable diet.
166 Similarly, higher agricultural yields reduce land pressure, and thereby also reduce the perceived
167 need to transition to a sustainable diet. Scenario combinations involving higher future yield and/or
168 SSPs with lower population size cause sustainable consumers to decline, which means that land use
169 ends up being higher than it would be without this feedback between land use and dietary choices.

170 Continental and country-level land use projections

171 Projections broken down by geopolitical region reveal significant heterogeneity behind the global
172 trends (Figure 2). Europe and Oceania exhibit an increase in sustainable consumers and a decrease
173 in land use across all SSPs. This is because countries in Europe and Oceania have lower inferred
174 barriers to adopting a sustainable diet (σ_i) compared to the rest of the world (Appendix SI Figure 6).
175 With respect to evolution of global land use, they always remain in the regime where sustainability
176 is the dominant behaviour with higher utility. The relative ordering of land use by SSP we saw in
177 the global projections remains consistent at the continent level. These projections also show that
178 an increase in sustainable consumers will not necessarily lead to a decrease in land use, even if that
179 is the general trend.

180 For example, in certain scenarios, Africa, Asia and the Americas show a decrease in land use
181 (with respect to 2013) while the fraction of sustainable consumers also declines, on account of
182 growth in agricultural yield outweighing the effects of income and population growth. For these
183 regions, projections under the SSP3 scenario shows the highest use of land. This is because, for
184 them, population projection under SSP3 is the highest among all SSP scenarios (unlike Europe
185 and Oceania where it is the lowest). That, coupled with a steady decline in sustainable consumers
186 in their population, results in the fastest change in land use. For these regions, the average socio-
187 economic barrier to adopting a sustainable diet is always higher compared to the evolution of
188 global land use in all of the 20 scenario combinations. This indicates that future yield, income and
189 population do not drive the growth of sustainable consumers and the decline of land use identically.
190 The feedback loop between land use and dietary behaviours in our country-level model gets scaled
191 up to the regional level, too. In other words, each region shows a unique behavioural response to
192 change in global land use because of its unique social setting.

193 Some countries with relatively small population sizes are projected to emerge as front runners
194 of global land use (Figure 3). The correlation between population and land use is not absolute,
195 however (Figure 3b). In 2013, the countries that had a comparatively lower population but high
196 land use were Kazakhstan (population, 18 million), Saudi Arabia (33 million), Australia (25 million)
197 and Argentina (45 million). Ranking projection of land use shows that it is likely the fourth spot,
198 currently occupied by Russia, will be taken over by Saudi Arabia by 2050 (which, in 2013, occupied
199 the fifth spot in land use) (Figure 3a). In 2013, the two countries consumed comparable areas
200 of global agricultural land for their respective demands (123 million hectares for Russia and 105

201 million hectares for Saudi Arabia). The primary reason for Saudi Arabia overtaking Russia can
202 be identified from Figure 3c. Russia sees an increase in sustainable consumption over the time
203 horizon, while Saudi Arabia sees a decrease. In all the scenarios, their baseline parameter value of
204 σ (barrier to adopting a sustainable diet) places them on opposite regimes of behavior with respect
205 to evolution of global land use.

206 Synergies can reduce peak global land use

207 We found that socio-economic factors as represented in our model—the social learning rate (κ), the
208 barriers to adopting a sustainable diet (σ), and income elasticity (h)—have very large impacts on
209 peak global land use, often ranging in the giga-hectares (Figure 4). This is particularly true when
210 higher incomes, higher population sizes and lower future yields force individuals to make a choice
211 between sustainable and unsustainable diets in the face of rapidly expanding global land use. In
212 contrast, when land use does not expand as rapidly due to lower population sizes or higher yields,
213 the perceived need to switch to a sustainable diet is less.

214 When future yields are lower ($f = 0.8$), the peak global land use is much more sensitive to social
215 processes than when future yield is higher ($f = 0.2$) (Figure 4). Low yield means rapidly expanding
216 land use, which in turn stimulates a social response in favour of wider adoption of a sustainable
217 diet. Hence in this scenario, changes in social parameters governing the pace and desirability
218 of change have large impacts on land use. When future yields are low, population growth also
219 becomes a determining factor in assessing the effectiveness of varying social parameters (Figure
220 4d). In contrast, when future yield is high, land use is lower even though more individuals are
221 practicing an unsustainable diet, and thus changes to parameters governing pace and desirability
222 of a sustainable diet have less impact.

223 In scenarios where future yields are lower, an increase in the social learning rate (κ) leads to high
224 peak global land use due to faster conversion to unsustainable consumption as per capita income
225 rises (Figure 4a). Globally, the barrier to adopting a sustainable diet is too high for sustainability
226 to spread in populations even when global land use increases quickly. In the model, if a sustainable
227 consumer samples their population very often (high social learning rate, κ), they are easily tempted
228 to shift to unsustainable consumption because they see an increased expected utility in switching.
229 The only way to reduce this effect is to reduce the barrier to adopting a sustainable diet (lowering
230 σ , Figure 4b). This could be possible by incentivizing consumption of plant protein by reducing
231 the market price of animal protein substitutes or increasing public knowledge about health and
232 environmental implications of a high meat diet. Once the barrier to adopting a sustainable diet is
233 sufficiently low, social learning rates assist in lowering the peak global land use (Figure 4b). When
234 σ is lowered, sustainable consumption becomes the dominant behaviour due to its higher utility. In
235 this case, a considerable amount of land is saved even in scenarios where global population growth
236 rate is high (SSP3) and future yields are inferior ($f = 0.8$).

237 If global land use evolves very slowly due to slow population growth (SSP1, SSP5) and high
238 global yield ($f = 0.2$), the model predicts that sustainable consumption never becomes the dominant
239 behaviour at the global level. This is because L always remains significantly lower to the baseline
240 values of σ in these scenarios. Even with sizeable changes in social parameters, κ and σ , only an
241 insignificant increase in sustainable consumers is achieved. As a result, there is no direct impact on
242 peak global land use. As global land use change is small in these scenarios (and sometimes negative,
243 see Figure 1a), there is not enough incentive for individuals to even pay a lowered cost to being
244 sustainable. In such a setting, the key to reducing global land use lies in the consumption patterns
245 of highly prevalent unsustainable consumers. Since global average income is high in these scenarios,
246 an increase in income elasticity can potentially cause negative impacts on global agricultural land

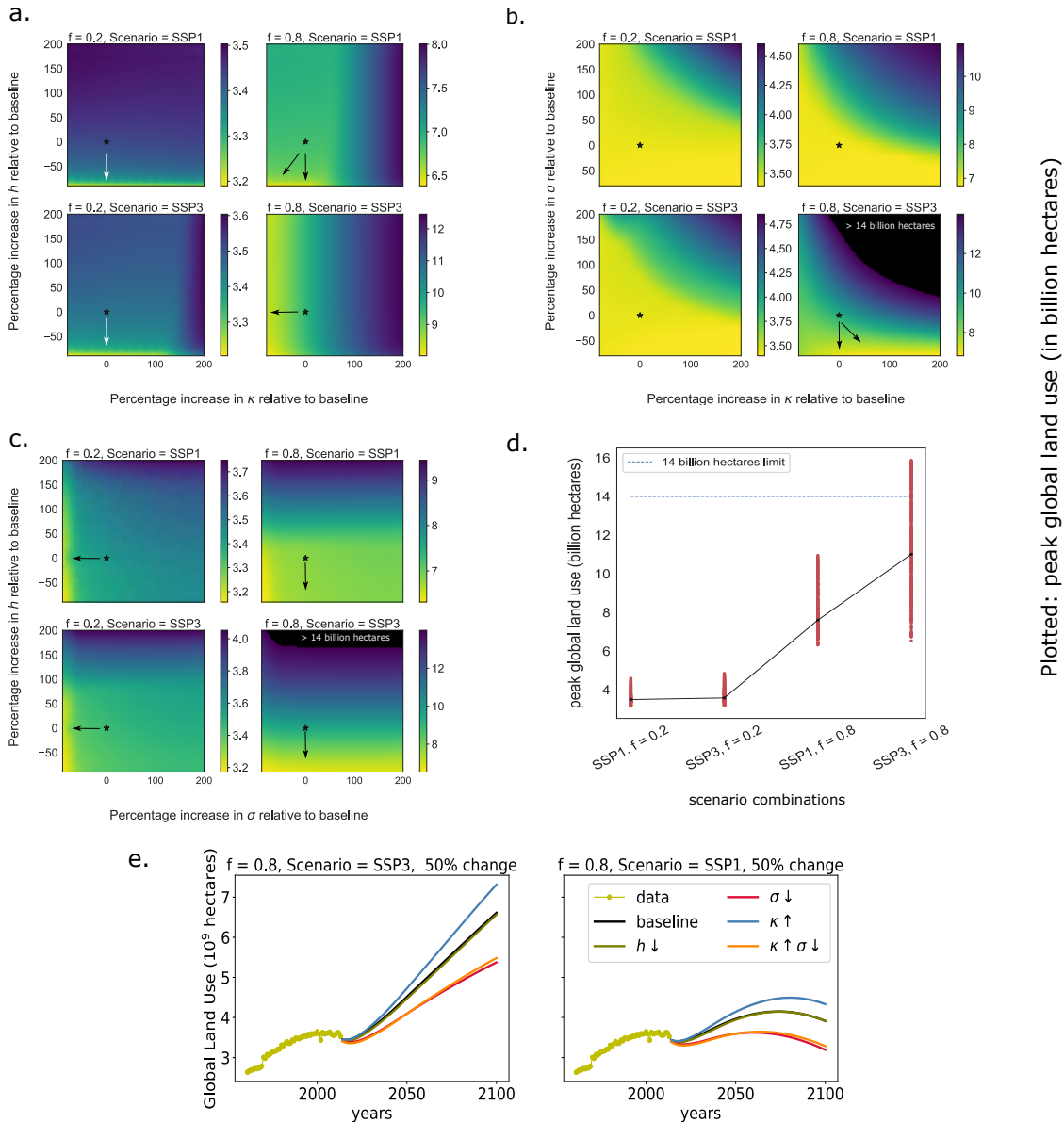


Figure 4: Variations in social parameters from baseline level impact global land use. Model output of peak global land use at four scenario combinations - $f = 0.2, \text{SSP1}$, $f = 0.2, \text{SSP3}$, $f = 0.8, \text{SSP1}$ and $f = 0.8, \text{SSP3}$. Model projections are evaluated at parameters deviated from their baseline settings. The black star in each plot indicates the position of the baseline parameter in the heat map. Heat map for peak land use projection with deviations in **(a)** κ (social learning rate) and h (income elasticity of food consumption), **(b)** κ and σ (barrier to adopting a sustainable diet), and **(c)** σ and h . All other parameters held at baseline values. The unit for the color bar in the heat-map is billion hectares. **(d)** Peak global land use values from (a)-(c) plotted versus the scenarios. **(e)** Model time series of global land use in the 21st century in scenarios of low global yield; parameters varied within 50% of baseline value.

247 use (Figure 4a, 4c).

248 However, in the least optimistic scenarios (high population growth rate and low future yields),

249 certain variations of social parameters from their baseline values can alter peak global land use by
250 approximately two billion hectares (twice the size of China). Depending upon socio-economic and
251 yield growth scenarios, the optimal strategy for lowering peak land use changes. Although it is
252 always beneficial to reduce the barrier to adopting a sustainable diet, there can be scenarios where
253 better gains are achieved by modulating the consumption patterns of unsustainable consumers.
254 Varying all three social parameters guarantees a synergy in terms of lowering of peak land use
255 in the 21st century, irrespective of socio-economic scenario, while varying only two of the three
256 parameters sometimes has little effect.

257 Discussion

258 Individual diets are influenced by complex social factors such as religion, concern for health, ur-
259 banization, female participation in labour, food prices, and sustainability practices [41, 42, 43, 44].
260 Several of these factors imply a two-way feedback between land use and dietary decisions. Here
261 we focused on the effect of ballooning global land use as a stimulus for individuals to adopt more
262 sustainable diets, against a backdrop where rising incomes also permits individuals to opt for un-
263 sustainable diets instead by eating more land-intensive foods such as meat. We subsumed other
264 factors in decision-making into our phenomenological parameters at the social (κ , σ) and individual
265 (h) level that we inferred from data.

266 We showed how coupled social-land dynamics can have giga-hectare impacts on land use, espe-
267 cially when future yield is low and/or population size is high, and we explored changes to social
268 parameters that minimize future land use under various scenarios for socio-economic development
269 pathways and future agricultural yield. We found that reducing barriers to adopting sustainable
270 diets is an important way to reduce peak global land use. Increasing social learning rates holds the
271 potential to accentuate the mitigating effect of reducing socio-economic barriers (a simultaneous
272 effect shows a reduction of 2 billion hectares in peak global land use). Increasing social learning
273 can result in negative effects if no improvements in lowering barriers are made, however.

274 Our minimal model made simplifying assumptions that could impact its land use projections.
275 For instance, we did not include aquatic sources of food, we ignored the influence of institutions,
276 and we assumed a binary classification of consumption behaviour. A future extension of our model
277 could include aspects of population heterogeneity such as a continuous behavioural spectrum along
278 with age and gender structure. Future work could also explore the effects of social norms in order
279 to determine how social inertia can accelerate or decelerate behavioural changes, as well as social
280 learning between countries. For the purpose of simplicity in working with country level data, we
281 also assumed homogeneous behaviour within each country by assigning unique parameter values
282 to every country, and this could be relaxed in future research. Similarly, given the enormous
283 greenhouse gas impacts of livestock [45], a future social process model would take into account the
284 perceived risk of climate change in modeling the behavioural drivers of a population.

285 Future research in coupled social-land use models can incorporate increasing sophistication
286 to deepen our understanding of social processes around dietary choices and land use dynamics,
287 as well as their interaction with other socio-economic factors and other environmental dynamics
288 such as climate change. These models could inform land use projections and deepen our insights
289 into relevant processes, by incorporating the driving mechanisms behind our dietary choices and
290 accounting for how they respond to changes in land use and socio-economic variables.

291 Methods

292 Coupled social-land Use Model

293 For a country i and year t , we assume two possible diet types: sustainable and unsustainable for
 294 the entire population. The sustainable diet type requires $c_i^S(t)$ hectares per capita to generate
 295 while the unsustainable diet requires $c_i^U(t)$ hectares per capita. By definition, $c_i^S(t) < c_i^U(t)$ for all
 296 i and t . We make the assumption that the sustainable diet is within reach of anyone in a country
 297 irrespective of income whereas unsustainable is aspiration-only. When income is small, individuals
 298 aspiring to an unsustainable diet are only able to include occasional land-intensive items in their
 299 diet, but as their income rises, they include more. We represent this behaviour with the following
 300 equation:

$$c_i^U(t) = (c_i^{U,max}(t) - c_i^S(t))(1 - e^{-h_i(m_i(t) - m_i^0(t))}) + c_i^S(t) \quad (1)$$

301 Where $c_i^{U,max}(t)$ is upper limit of consumption by the unsustainable practitioners, $m_i(t)$ is the
 302 average income of the population and $m_i^0(t)$ is the minimum income that can afford the sustainable
 303 diet at i in t . The parameter h denotes the elasticity in the behaviour of unsustainable practi-
 304 tioners. If h is large, c^U grows towards $c^{U,max}$ faster with income as compared to when h is small.
 305 Note that when average income $m_i(t)$ equals $m_i^0(t)$, the entire population consumes sustainably;
 306 that is, they consume $c_i^S(t)$ hectares per capita. The per capita consumption of practitioners of
 307 unsustainable diet, c_i^U , approaches $c^{U,max}$ asymptotically as the difference between m_i and m_i^0 gets
 308 higher. Our assumption that meat and dairy consumption increases with income has been explored
 309 and identified in earlier papers like [46, 41].

310 Let $x_i(t)$ and $1 - x_i(t)$ be respectively the proportions of the population that are practitioners
 311 and non-practitioners of sustainable diets in i at t . The average per capita consumption of the
 312 population can then be defined as follows:

$$c_i(t) = x_i(t)c_i^S(t) + (1 - x_i(t))c_i^U(t) \quad (2)$$

313 If $P_i(t)$ is the population of i in t then the land used due to dietary consumption of population
 314 i at t is $P_i(t)c_i(t)$. Global land use, or, the land used due to consumption by the entire population
 315 of the globe at t can then be defined as the sum of land consumed by all the nations in the world
 316 at t :

$$L^G(t) = \sum_i P_i(t)c_i(t) \quad (3)$$

317 We use imitation dynamics from evolutionary game theory to describe the time evolution of x_i .
 318 The utility gain for changing from an unsustainable diet to a sustainable diet for the baseline model
 319 is given by

$$\Delta e = \alpha_i L^G(t) - \sigma_{0,i}$$

320 Hence, as the impact function $L^G(t)$ rises over time due to growing incomes, there is a growing
 321 incentive for individuals to switch to a sustainable diet, according to a proportionality constant
 322 α_i . The rate of switching becomes faster as the difference between $\alpha_i L^G - \sigma_{0,i}$ grows and vice
 323 versa. However, this behaviour to switch to sustainable practice is only effective when $\alpha_i L^G$ is
 324 greater than $\sigma_{0,i}$. When $\alpha_i L^G$ is less than this threshold, $\sigma_{0,i}$, the proportion of unsustainable
 325 practitioners grows, the rate being determined by the absolute difference between $\alpha_i L^G - \sigma_{0,i}$. We

326 call the parameter $\sigma_{0,i}$, the socio-economic barrier to adopting a sustainable diet in i . Assuming a
327 social learning rate of $\kappa_{0,i}$ for i we can write the evolution of sustainable practitioners as follows:

$$\frac{dx_i}{dt} = \kappa_{0,i}x_i(1 - x_i)\Delta e, \quad x_i(t_0) = x_{0,i} \quad (4)$$

328 After some rescaling of parameters we obtain:

$$\frac{dx_i}{dt} = \kappa_i x_i(1 - x_i)(L^G(t) - \sigma_i), \quad x_i(t_0) = x_{0,i} \quad (5)$$

329 Where $\kappa_i = \kappa_{0,i}\alpha_i$ and $\sigma_i = \sigma_{0,i}/\alpha_i$ are the rescaled parameters. We refer to the rescaled
330 parameters κ_i and σ_i with their original names. That is, κ_i is social learning rate and σ_i is the
331 barrier to adopting a sustainable diet in i . When global land use $L^G(t)$ exceeds σ_i , unsustainable
332 practitioners switch to sustainable behavior at a rate which is determined by κ_i , the existing
333 proportion of sustainable practitioners and the absolute difference between global land use and σ_i .
334 When global land use is less than σ_i , sustainable practitioners switch to unsustainable behaviour
335 through the same mechanism.

336 Method for calculating $c_i^{U,max}(t)$ and $c_i^S(t)$

337 The upper bound of per capita consumption, $c^{U,max}$, is calculated by assuming that the maximum
338 diet is the one that allows highest intake of items that belong in the meats and dairy diet groups.
339 Similarly, for c^S , we assume that sustainable diet is the one that allows least consumption of items
340 in those groups. Our assumption is backed by numerous studies that have found meat intensive
341 diets to be environmentally unfriendly and land-intensive [18, 47]

342 $c^{U,max}$ and c^S can be calculated between 1961 and 2013 for countries whose data is reported
343 in FAOSTAT's food balance sheets [1]. We categorize each of the 21 food items listed in the food
344 balance sheets into one of the seven groups of diet - fruits, vegetables, grains, meats, dairy, oils and
345 sugar.

346 For every country i , we calculate its maximum possible diet by replacing its average consumption
347 of items in the 'meats' and 'dairy' groups (in kcals/capita/day) with the consumption values of the
348 countries that consumed the most of those items that year. Similarly, for the minimum sustainable
349 diet, we replace them with the consumption values of countries that consumed the least of those
350 items in that year. Values for the remainder of the diet (i.e the other groups - fruits, vegetables,
351 grains, sugar, oils), remain the same as reported data. An example of such a construction is shown
352 in Appendix SI Table 1). The method of evaluating these bounds are explained with more detail
353 in Appendix SI Section 1.1.

354 Once these hypothetical maximum and sustainable diets are constructed for a country i , we
355 use the model developed in Ref. [2] to calculate the total land required to generate that per capita
356 dietary demand for the population of i in t (see Appendix SI Section 2 for an overview of this
357 model). We divide the output of the model with the population of i at that year to obtain per
358 capita land use equivalent of the hypothetical diet ($c^{U,max}$ if maximum diet, c^S if sustainable diet).

359 In order to evaluate these values for years beyond 2013 (for purpose of projections), we use an
360 extrapolating parametric function (See Method section for f scenarios).

361 Definition of land use: Data and Methods

362 We use the model developed in [2] to generate the country-level time series data of average per
363 capita land use between 1961 and 2013. The model is described briefly in Appendix SI Section
364 2. The UN FAOSTAT data-set also provides country level data for land used on agriculture and

365 pasture land. However, this is not the same as our definition of ‘land use by i ’. This is because
366 countries are not entirely self-dependent in providing for their food demand. Consume in i can
367 be partly produced in j and vice-versa. Since the model in [2] accounts for differential yields of
368 food sources, the data for per capita land use, as generated by model in [2], accounts for land
369 used from across the globe to provide for the consumption in i . If two countries have similar
370 dietary consumption, the country which has a lower effective yield has higher value of per capita
371 consumption than the country which has a higher value of effective yield.

372 In all our projections and analysis, we consider land that is required to generate the food that
373 ends up being consumed by humans. Land equivalent of food wastage is not considered in our
374 calculations. The data reported by UN FAOSTAT’s land statistics division [48] accounts for land
375 used for all agricultural purposes. This includes land equivalent of food wastage. In Appendix SI
376 Figure 1, we see the quantitative difference between their time-series and our global model output.
377 FAOSTAT estimated that 1.4 billion hectares were lost due to food wastage in the year 2007 [49].
378 This number matches exactly with the difference between the two series at 2007 in Appendix SI 1.

379 **Population, income and f (yield) scenarios:**

380 We borrow the SSP scenarios (Shared Socioeconomic Pathways) introduced in [39] for projecting
381 population and income to 2100. A number of existing models are compiled in the SSP Public
382 Database hosted by the International Institute for Applied System Analysis (IIASA). Among them,
383 we choose the OECD Env-Growth Model [40] for obtaining future projected values of country level
384 population and income. In Appendix SI Section 4 we discuss the inclusion procedure of countries
385 in our analysis. There we provide reasons for the exclusion of certain countries from the analysis.
386 The choice for OECD Env-Growth was made because it covers projections for maximum number
387 of countries among the existing models.

388 The bounds for maximum and minimum per-capita consumption ($c^{U,max}$ and c^S) are projected
389 into the future with a parametric function. The parameter f , a number between 0 and 1, represents
390 scenarios of yield future. We now explain the meaning of a yield scenario parameterized by f . If the
391 trend of $c^{U,max}$ and c^S between 1990 to 2013 is decreasing (which is more often than increasing),
392 the series can at least reach f times its 2013 value in the future. Similarly, if the trend is increasing,
393 it can reach at most $1 + f$ times its 2013 value in the future. The rate at which a projected curve
394 (either $c^{U,max}$ or c^S) reaches towards its bound is determined by its rate between 1990 and 2013.

395 Let c be the concerned time series that we wish to project till 2100 using our parametric function.
396 The series c can either be $c^{U,max}$ or c^S for a country i . The series is always defined between 1961
397 and 2013. First, we fit an exponential of form $y = ae^{bt}$ to a truncated c series. This truncated
398 version of c is the time series of c from 1990 to 2013. If $b < 0$ we call the series trend decreasing
399 and if $b > 0$ we call the series trend increasing. Here, a and b are constants. We extrapolate the
400 time series c till 2100 (starting from 2013 onward) using the following equations:

$$c(t) = \begin{cases} c(2013) - (c(2013) - c(2013)f)(1 - e^{-\beta(t-2013)}), & \text{if initial trend is decreasing} \\ c(2013) + c(2013)f(1 - e^{-\beta(t-2013)}), & \text{if initial trend is increasing} \end{cases}$$

401 Here f is the tune-able parameter - a real number between 0 and 1 that defines the future yield
402 scenario. For the above equation, t is always greater than 2013. The exponent β is adjusted such
403 that continuity is maintained at 2013 between the initial trend, ae^{bx} , and the projected trend $c(t)$.

404 That is,

$$\beta = \begin{cases} -\frac{1}{c(2013)} \frac{abe^{2013b}}{1-f}, & b < 0 \\ \frac{abe^{2013b}}{c(2013)f}, & b > 0 \end{cases}$$

405 In Appendix SI Figure 9 , we show two examples of $c^{U,max}$ and c^S projection till 2100 using
406 the above method. The two countries that are chosen as examples are USA and Netherlands. USA
407 shows a decreasing initial trend ($b < 0$) whereas Netherlands shows an increasing initial trend (b
408 > 0).

409 If we assume that maximum and sustainable dietary distributions (in kcals/capita/day) for
410 countries remain constant from 2013 onward, f scenarios represent scenarios of yield future. Then,
411 a low f value represents improvement towards high yield values. A high f value represents decel-
412 eration of yield rates, causing them to converge to inferior future values.

413 Parameter plane analysis

414 The three social parameters, κ , σ and h are varied from their baseline values in a pairwise fashion
415 while keeping the third parameter fixed at the baseline setting. Every parameter is varied from
416 -100% to 200% of its baseline value. That is, if α is a social parameter, we vary it from 0 to 3α
417 while conducting this analysis.

418 Since we begin projecting at 2011 and continue till 2100, we make the corresponding changes
419 in social parameters at 2011 and keep them that way for the entirety of the projecting period. We
420 make equal percentage changes to social parameters of all countries included in our model. In the
421 parameter planes, we observe the effect of changes in parameter values on peak global land use
422 attained between 2011 and 2100.

423 We show results for four scenario combinations - i) SSP1, $f = 0.2$, ii) SSP3, $f = 0.2$, iii) SSP1,
424 $f = 0.8$ and iv) SSP3, $f = 0.8$. In all the parameter planes, the colors represent the value of peak
425 global land use (based on an accompanying color-bar). All units of peak global land use are in
426 billion hectares. Baseline parameters are marked by a black star (no change) in each parameter
427 plane. Arrows indicate direction towards least peak global land use.

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