

## Coupled social and land use dynamics affect dietary choice and agricultural land-use extent

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Dietary patterns have long been a driver of global land use. Increasingly, they also respond to it, in part because of social processes that support adoption of eco-conscious diets. Here we develop a coupled social-and-land use mathematical model parameterised for 153 countries. We project global land use for future population, income, and agricultural yield using our coupled dynamical model. We find that coupled social-and-land feedbacks can alter the peak global land use for agriculture by up to 2 billion hectares, depending on the parameter regime. Across all yield scenarios, the model projects that social dynamics will cause an increase in eco-conscious dietary behaviour until the middle of the 21st century, after which it will decline in response to declining land use caused by a shrinking global population. The model also exhibits a regime of synergistic effects whereby simultaneous changes to multiple socio-economic parameters are required to change land use projections. This research demonstrates the value of including coupled social-and-land feedbacks in land use projections.

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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 per day to 2600 kcal per day over this period<sup>1</sup>. Land is the primary source of the 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<sup>2</sup>. 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 the clearing of forests and habitat fragmentation<sup>3,4</sup> to increased greenhouse gas emissions<sup>5,6</sup>.

Agricultural intensification faces an uncertain future. From 1961 to 2013, production gains were mostly due to the steady growth in land productivity<sup>1,5</sup>. Some studies suggest that certain major crops are approaching their yield ceilings in rich countries<sup>7–9</sup>. 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<sup>10</sup>. Slowing intensification may trigger agricultural land expansion if demand for food rises on account of growing populations and per capita income and if food production prices remain unchanged.

Mathematical models of sustainable food systems are becoming an increasing topic of research<sup>11–17</sup>. Research on sustainable pathways for agricultural technologies tends to focus on the supply side of the problem. On the demand side, models often stipulate future demand trajectories that are independent of how the model variables evolve. For instance, sophisticated land system ensemble models used to project land use in Intergovernmental Panel on Climate Change (IPCC) reports use scenarios for homogenized dietary consumption patterns as inputs and, as such do not study the dynamics of system-induced drivers of human consumption behaviors<sup>18–21</sup>. The importance of incentivizing sustainable, eco-conscious consumption has been noted<sup>22</sup>. Dietary patterns can heavily influence trajectories of global land use<sup>20,23–26</sup> and individuals include environmental factors while making dietary decisions<sup>27,28</sup>, and therefore land-use dynamics and socially influenced dietary choices are coupled to one another through two-way feedback. However, there has been limited investigation into understanding how these shifts in dietary patterns evolve within populations due to social and economic factors, and in particular how they respond to changing land use.

Eco-conscious consumption is an economically and socially induced process that evolves endogenously in a population and hence systematic study using theoretical models may help generate insights into this process. From the individual perspective, adopting an eco-conscious diet may involve paying the cost of losing the personal satisfaction of consuming meat<sup>29,30</sup>. However, an individual's choice to adopt an eco-conscious diet can promote environmental sustainability, since scarce global land use is reduced as a result of that choice (although we note that reduced land use for food production does not translate automatically into reduced pressure to convert natural land states since the land that is spared could still be used for other forms of natural resource extraction). Hence dietary choices represent a public goods game, where individuals may choose to contribute to a common benefit that all members of the group receive, even if they did not make a contribution<sup>31–33</sup>. Modeling social behavior in public goods games often uses models of social learning dynamics from evolutionary game theory, which captures how individuals learn behaviors from one another<sup>34–36</sup>. Interest has grown in coupling

dynamic social learning models to models of natural processes such as the global climate system<sup>37,38</sup> and terrestrial ecosystems<sup>39</sup> although social learning dynamic models have not been applied to study coupled dynamics of global land use for food production and dietary decision-making in human populations, to our knowledge.

Here, we introduce a modeling framework for coupling the country-level dynamics of eco-conscious dietary decision-making under social learning processes to country-level land-use dynamics. Our objectives are to: (1) show how models of social dynamics and land-use dynamics can be coupled to generate dynamics that are not possible using approaches that treat these systems in isolation from one another, and (2) gain insight into how potential coupled social-and-land use processes alter both projected global land use for food production and projected dietary trends. Our objective was not to generate projections for policy use, but rather demonstrate that the framework has potential for such applications in the future. Hence, we opted for a minimal model that was easier to fit to data and gain insight from.

## Results

**Model overview.** Our mathematical model describes a social learning process by which individuals learn dietary behavior from others. Our model captures the two-way feedback between land use and dietary practice: as dietary practices impact global land use for food production, the resulting trends in global land use can, in turn, stimulate behavior toward more eco-conscious diets in a closed feedback loop, albeit modified by socio-economic drivers. Details of the model appear in “Methods”.

We compare diets by comparing the per capita land required to support them. For every country  $i$ , we assume a proportion  $p_i(t)$  of the population is below the poverty line (where  $t$  is time, in years). These individuals eat a sustenance diet that requires an amount of land  $c_i^s(t)$ , measured in hectares per individual for production. In contrast, the proportion  $1 - p_i(t)$  of the population above the poverty line can choose either an eco-conscious diet or a land-intensive diet. We define a daily diet to be eco-conscious if it uses between  $c_i^s(t)$  and  $c_i^l(t)$  hectares of land per capita, where  $c_i^l(t)$  is the land use required to support the eco-conscious EAT-Lancet diet<sup>40</sup>. We assume that no diet requires less land than the sustenance diet for its support. A diet is land-intensive when it requires more than  $c_i^l(t)$  hectares per capita to maintain. The actual per capita land use due to the diet of an average individual above the poverty line in country  $i$  is denoted  $c_i^A(t)$ , and this quantity depends on how many individuals in that country practice eco-conscious versus land-intensive diets. Further details on how this quantity is inferred appear in the Methods section.

We couple global land use for food production and population dietary behavior by developing an evolutionary game theory model that accounts for social learning and socio-economic incentives for individuals above the poverty line to switch between eco-conscious and land-intensive diets. Individuals shift from a land-intensive diet to an eco-conscious when the personal utility of the eco-conscious diet outweighs the personal utility of the land-intensive (and vice versa). The rate of dietary change is dictated by (a) this difference in utilities at any given time  $t$  and (b) a social learning rate that describes how quickly social learning of behavior occurs in country  $i$ . In particular, the proportion  $x_i(t)$  of the population eating an eco-conscious diet at time  $t$  in country  $i$  is

$$\frac{dx_i}{dt} = \kappa_i x_i (1 - x_i) (\beta_i m_i(t) + \alpha_i + L^G(t)) . \quad (1)$$

Here,  $\kappa_i$  is the social learning rate, and  $\Delta e_i = \beta_i m_i(t) + \alpha_i + L^G(t)$  represents the utility difference that governs dietary change.

When  $\Delta e_i > 0$ , the proportion  $x_i$  of individuals in country  $i$  eating an eco-conscious diet increases, but when  $\Delta e_i < 0$ , that proportion decreases. The term  $L^G(t)$  is the global land use for food production. When  $L^G(t)$  becomes sufficiently large,  $x_i$  increases since greater observed land use can stimulate a switch to eco-conscious diets.  $m_i(t)$  is the average per capita income of country  $i$  and the parameter  $\beta_i$  controls the impact of per capita income on dietary decision-making. For instance, if higher per capita incomes cause more individuals to eat land-intensive diets, then  $\beta_i$  may be negative, causing a decline in  $x_i$ . Finally, the parameter  $\alpha_i$  is the net utility (benefit minus cost) for an individual to adopt an eco-conscious diet associated with all other factors not captured by  $\beta_i$  or  $L^G$ . This is the combined effects of various psychological, social and economic factors (and maybe negative). When  $c_i^A > c_i^L$ , negative values for  $\alpha_i$  and  $\beta_i$  indicate a higher net benefit of a land-intensive diet over an eco-conscious diet. For simplicity, we call  $\alpha_i$  and  $\beta_i$  the net non-income benefit and the net income benefit of adopting a land-intensive diet over an eco-conscious diet respectively hereafter (since their inferred values tend to be negative in most countries). The rate of dietary change is dictated by  $\kappa_i$ , which describes how fast social learning occurs in country  $i$ . The parameter  $\kappa_i$  acts as a control knob that determines how often individuals ‘sample’ other individuals in the population regarding their diet. A high value of  $\kappa_i$  can accelerate change in either direction depending on the sign of the utility difference. A graphical representation describing the coupled two-way feedback model between global land use and individual dietary behavior in populations is represented in Fig. 1.

We use a previously published model<sup>2</sup> to generate country-level land use data based on dietary patterns from 1961 to 2013. The model we use to generate the country-level land-use data takes into account that food consumed in a country may come from imported sources. Therefore, the model computes global land used due to dietary consumption by a country at a year by adding the land used inside the country (accounting for locally produced food) and land used outside the country (accounting for imported food). We fit our model to these data to estimate  $\kappa_i$ ,  $\beta_i$ , and  $\alpha_i$  for 153 currently existing countries (see Supplementary Methods for methods of parameter estimation and Supplementary Note 1 for results of parameter fitting). These estimated parameters were taken as our baseline parameter values. Under the umbrella term “agricultural land use” we included land used for agriculture, pasture, and feed generation. Our land calculations excluded land equivalent of food wastage: we accounted only for the land that is used to generate the food that ends up being consumed by the population (see “Methods” for details). Beyond 2013 (the last available year in the Food and Agricultural Organization data—FAOSTAT, food balance sheets<sup>1</sup>), land use was projected under different scenarios defined by a parameter  $f$  for future yields (a number between 0 and 1). Low values of  $f$  represent scenarios where future global yields are higher. High values of  $f$  represent inferior (low) yield futures (see Methods for a mathematical representation of the scenarios).

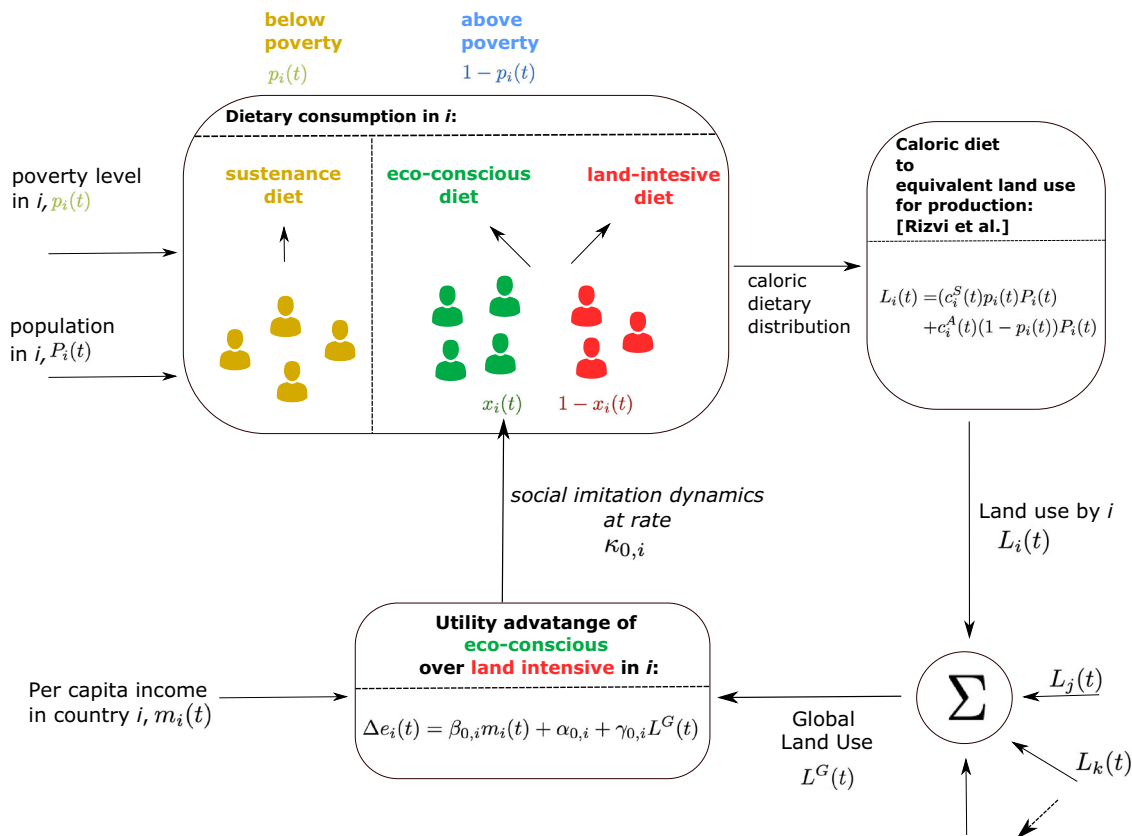
We make projections of global land use for food production (hereafter, simply “global land use”) for 20 scenario combinations for 153 countries (see Supplementary Note 1 for details on countries included for projection analysis). For country-level population size and income projections, we use the five SSP (“shared socio-economic pathway”) scenario markers, SSP1–SSP5<sup>41,42</sup>. Each SSP scenario represents a unique storyline for the future that dictates the trajectory of population and income in countries (among other things). For our main results we assumed SSP2, where current trends of population and income continue, and moderate progress is made by achieving income convergence between countries. We present results for

the other four SSPs in the Supplementary Information (Supplementary Fig. 8). SSP1 is characterized by relatively high income and small population. SSP3—also called the road to regional rivalry—is characterized by an overall high population growth and low-income levels in developing countries. The SSP4 future sees a high disparity in economic growth rates between high-income and low-income countries; global growth is less rapid compared to SSP1. In an SSP5 world, economic development is of utmost priority, income growth is high, on average, and it is coupled with strong improvement in education that leads to reduced fertility and hence a relatively small but well-educated population. See Supplementary Fig. 7 for population and income projections under the five SSP scenarios until 2100. Although each SSP scenario has a unique storyline for yield growth, we also show results for four possible future agricultural yield trajectories that differ from the baseline SSP scenario assumption:  $f=0.2$  (high future yields), 0.4, 0.6, and 0.8 (low future yields). Our use of SSP scenario is selective and they only serve as a starting point to explore parameter variations: as we only use population and income projections from the SSP scenarios and not yield, our projections for every SSP scenario differs from conventional approaches to projecting land use under these scenarios.

**Social-and-land dynamics at the global level.** Model projections at the global level reveal two main findings. The first main finding is that the proportion of eco-conscious consumers (the proportion of individuals above the poverty level practicing an eco-conscious diet) is predicted to rise in response to growing global land use until the middle of the 21st century, and then start declining as global land use also declines (Fig. 2). The peak global land use falls between 3.25 and 4.5 billion hectares, depending on the yield scenario, and the proportion of eco-conscious consumers peaks between 45% and 53%, depending on yield. This effect persists in most of the other SSP scenarios (see Supplementary Fig. 8) except that in SSP3 at very low future yields, there is no decline but a saturation in the proportion of eco-conscious consumers.

This behavior can be explained in terms of the utility function in our model that determines decision-making ( $\Delta e$ , Eq. (3)). Almost every country included in our analysis has a negative fitted value for  $\alpha_i$  and  $\beta_i$  (see Supplementary Data 1), meaning that there is both a net cost for practicing an eco-conscious diet, and higher incomes further tend to cause more individuals to adopt a land-intensive diet. When global land use  $L^G$  is close to its 2013 values, the net utility for adopting an eco-conscious diet is negative because  $\alpha_i$  and  $\beta_i$  are dominant (thus,  $\Delta e < 0$ ). However, between 2020 and 2050, global land use  $L^G$  increases substantially and dominates the utility (Fig. 2), therefore the sign of  $\Delta e$  is reversed for most countries. (More specifically, the proportion of the global population for which  $\Delta e > 0$  is greater than the proportion for which  $\Delta e < 0$ , see Supplementary Fig. 9). The global proportion of eco-conscious consumers declines after 2050 for all yield scenarios because declining global land use causes the utility for practicing an eco-conscious diet to become negative for a majority of the global population. A predicted decline in the global population size in the latter half of the century further contributes to a net decrease in global eco-conscious consumer proportion, since global land-use pressure is reduced as a result.

The rising and falling trend occur for all four yield scenarios. However, in the case of lower yield ( $f=0.6, 0.8$ ), the peak in the proportion of eco-conscious consumers occurs before the peak in global land use. Whereas for high yield ( $f=0.2, 0.4$ ), it occurs after. This difference occurs because land use expands rapidly under low yield scenarios, thus stimulating a more rapid social response.



**Fig. 1 A graphical representation of the coupled two-way feedback model between global land use and dietary behavior in populations.** We consider country-level populations. Each country has two subpopulations—the subpopulation below the poverty level and the subpopulation above the poverty level. The subpopulation below the poverty level in  $i$  (which occupies a fraction of  $p_i(t)$  of the total population in  $i$  at time  $t$ ) consumes a sustenance diet that requires a number of  $c_i^S(t)$  hectares individual<sup>-1</sup> land, globally, to be produced at time  $t$  (measured in years). The subpopulation above the poverty level in  $i$  can choose between an eco-conscious diet or a land-intensive diet (details can be found in Methods). It requires an amount of  $c_i^A(t)$  hectares individual<sup>-1</sup> land at time  $t$ , globally, to produce the average dietary consumption of the population above-poverty in  $i$ . The method for calculating  $c_i^A(t)$  can be found in Eq. (5). The method for converting a caloric diet to equivalent amount of land required to produce the diet can be found in Methods. Global land use at  $t$ , per-capita income in country  $i$  at  $t$ ,  $m_i(t)$ , and social parameters in  $i$ — $\beta_{0,i}$ ,  $\alpha_{0,i}$ ,  $\gamma_{0,i}$  determine the utility advantage of an eco-conscious diet over a land-intensive diet in  $i$ . The utility advantage  $\Delta e_i(t)$  along with the social learning rate,  $\kappa_{0,i}$  drive the social imitation dynamics that determines the rate of change of  $x_i(t)$ , the proportion of above-poverty sub-population in  $i$  consuming an eco-conscious diet.

The details of the rising and falling trend also vary considerably depending on the SSP scenario (see Supplementary Fig. 8).

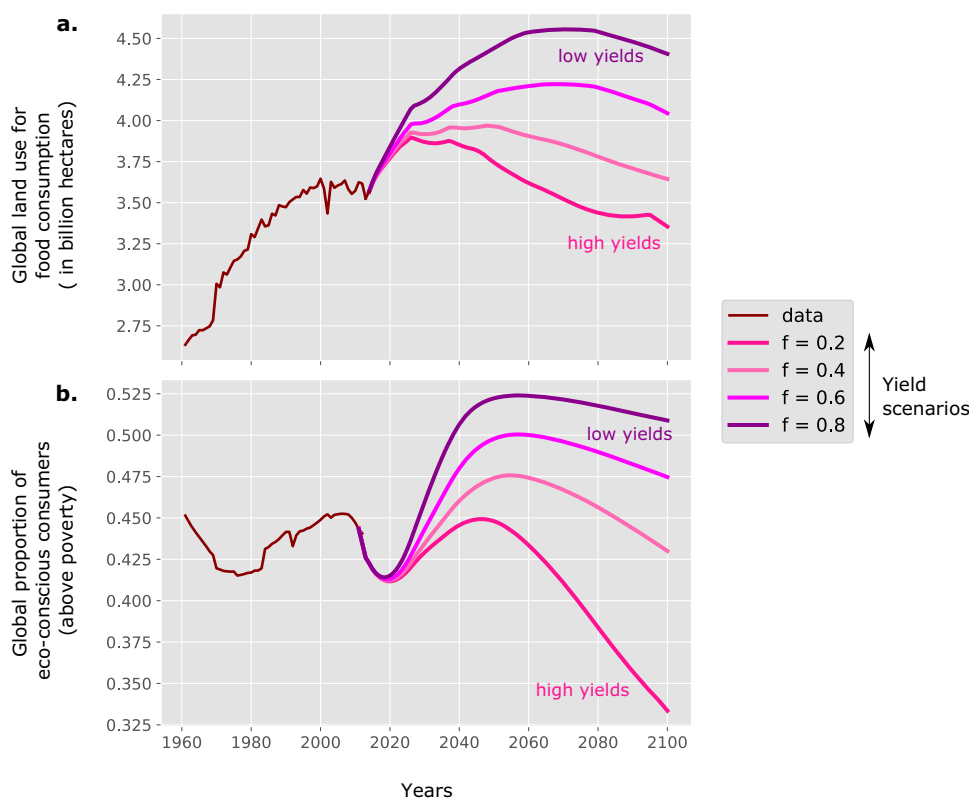
The second main finding from analyzing these global level projections is that the social dynamics partially counteract benefits of higher yield, or land use impacts caused by other trends such as changing per capita income and population size. Higher agricultural yields reduce land pressure, and thereby also reduce the perceived need to transition to an eco-conscious diet. As a result, the higher yield scenarios also have a lower proportion of eco-conscious consumers (Fig. 2).

**Heterogeneity in continent-level projections.** Projections broken down by geopolitical region reveal notable heterogeneity behind the global trends (Fig. 3, Supplementary Fig. 11). Only Africa is projected to continuously increase its land use (defined for our study as the proportion of global land use due to dietary choices in Africa) until 2100, for all yield scenarios. Asian land use increases until 2030 but then it falls continuously until 2100, at first because the proportion of eco-conscious consumers rises and then because its population size begins to decline. European land use peaks in 2040 but, unlike Asia, it exhibits a continuous increase in the proportion of eco-conscious consumers through 2100. Oceania and the Americas experience declining land use through most of the time period. For Oceania, the proportion of

eco-conscious consumers always increases while for the Americas, the proportion of eco-conscious consumers may increase or decrease depending on the yield scenario.

Heterogeneity in land use and eco-conscious behavior across continental aggregates is a combined result of continental variation in baseline parameters, the impact of global land use on sustainability decision-making, and variation in continental population size projections. For example, in certain yield scenarios, Europe sees a constant growth of eco-conscious consumers despite a decline in its own use of land for dietary consumption because it adjusts its behavior according to trends of global land use. Moreover, at the baseline level, its median value of  $\alpha_i$  is less negative compared to other continental groups (Supplementary Fig. 2). Due to this, there is a very low threshold of global land use for Europe across which its preference shifts to a more eco-conscious diet. The same behavioral pattern is seen for Oceania and the Americas (except the highest yield scenario  $f=0.2$ ) where an increasing or steady eco-conscious consumer proportion across all yield scenarios is met with a steady decline in land use. Unlike Europe, Oceania and the Americas see constant decline in land use throughout most of the projecting period in the baseline setting.

The population size of Africa increases steadily throughout the 21st century under the SSP2 scenario (see Supplementary Fig. 7).



**Fig. 2** Baseline global land use and global eco-conscious consumer proportion projections till 2100 under four yield scenarios and the population and income scenario of SSP2. Results are shown for yield scenarios ranging from high ( $f = 0.2$ ) to low ( $f = 0.8$ ) future yields at the SSP2 income and population scenario. The historical data for global land use due to food consumption and the corresponding global proportion of eco-conscious consumers (above poverty) are indicated with black lines in both the panels. The historical data is plotted from 1961 to 2013. See “Methods” and Supplementary Methods for more details on how these data are calculated. **a** Projections for global land use due to food consumption till 2100 under four yield scenarios at the income and population scenario of SSP2. **b** Projections for the corresponding global proportion of eco-conscious consumers till 2100 under the same four yield scenarios and the income and population scenario of SSP2. Compiled baseline projections for all the yield scenarios under all five SSP scenarios (a total of 20 combinations) can be found in Supplementary Fig. 8.

Several African nations have positive values of  $\beta_i$  and its median value for the social learning rate  $\kappa_i$  is also very low (see Supplementary Fig. 2). These result in most African countries experiencing a net cost for shifting to an eco-conscious diet. Thus, the proportion of eco-conscious consumers declines, or at best remains constant, in all yield scenarios (even when global land use increases rapidly) throughout the 21st century. This, coupled with constant population growth, causes a massive increase in land use in Africa at the baseline setting (an increase from 500 million to 1 billion hectares from 2013 levels).

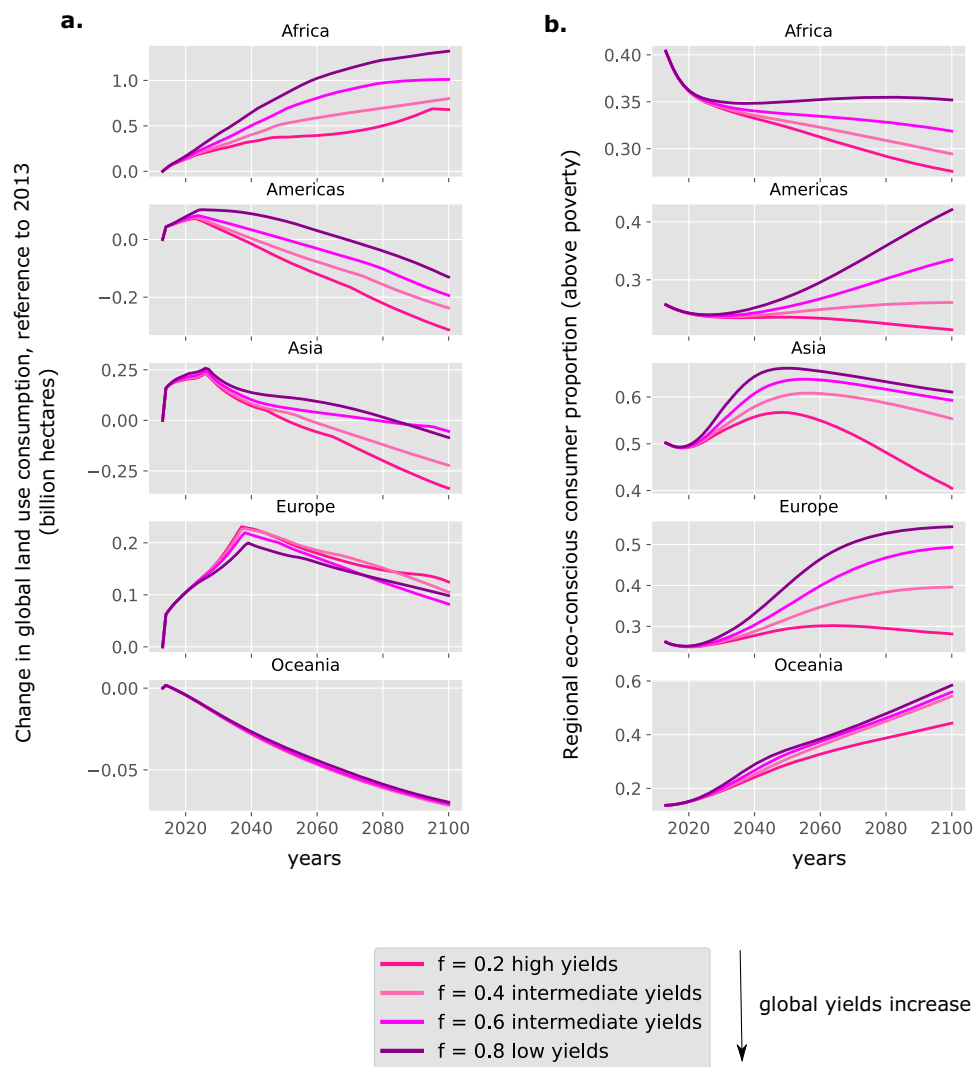
Despite having similar land-use patterns, the trajectories of the proportion of eco-conscious consumers for Europe and Asia show a subtle difference. Asia starts at a higher proportion of eco-conscious consumers than Europe but it soon saturates or goes down to lower levels. In comparison, Europe begins at a lower value but climbs up higher and begins to saturate near the end of the century. Despite having the same stimulus in the utility term from global land use, Europe reacts positively compared to Asia because of a higher median  $\beta_i$  (see Supplementary Fig. 2). As countries become wealthier over the 21st century in both Europe and Asia (under SSP2), Asian countries see a higher cost of shifting to an eco-conscious diet compared to European countries.

**Synergies can reduce peak global land use and delay peak year.** We found that socioeconomic factors as represented in our model—the social learning rate ( $\kappa_i$ ), and the income and the

non-income associated net benefit to adopting an eco-conscious diet ( $\beta_i$  and  $\alpha_i$ ) respectively—have very large impacts on peak global land use, often ranging in the giga-hectares (Fig. 4). In Fig. 4, we compare the effect of the parameter changes in high ( $f = 0.2$ ) and low ( $f = 0.8$ ) yield scenarios under SSP2. (Results comparing SSP2 and SSP3 can be found in Supplementary Fig. 10).

When future yields are lower ( $f = 0.8$ ), the peak global land use and peak year are much more sensitive to social processes than when future yield is higher ( $f = 0.2$ ) (Fig. 4). Low yield means rapidly expanding land use, which in turn stimulates a social response in favor of wider adoption of an eco-conscious diet. Hence in this scenario, changes in social parameters governing the pace and desirability of change have large impacts on land use. When future yields are low, population and income growth also become determining factors in assessing the effect of changing social parameters (see Supplementary Fig. 10 for comparison between SSP2 vs. SSP3). In contrast, when future yield is high, peak land use is lower even though more individuals are practicing a land-intensive diet, and thus global land use  $L^G$  is out of the range of values where it can stimulate social change, at least under the range of values for  $\alpha_i$  and  $\beta_i$  we explore in Fig. 4.

The social learning rate ( $\kappa_i$ ) has a limited impact on peak global land use when  $\beta_i$  or  $\alpha_i$  are above their baseline value (Fig. 4a, b, d, e). But when they are below their baseline value, a sufficiently large social learning rate causes peak land use to jump, for instance from 3.5 (blue) to 6 giga-hectares (yellow) in the low yield



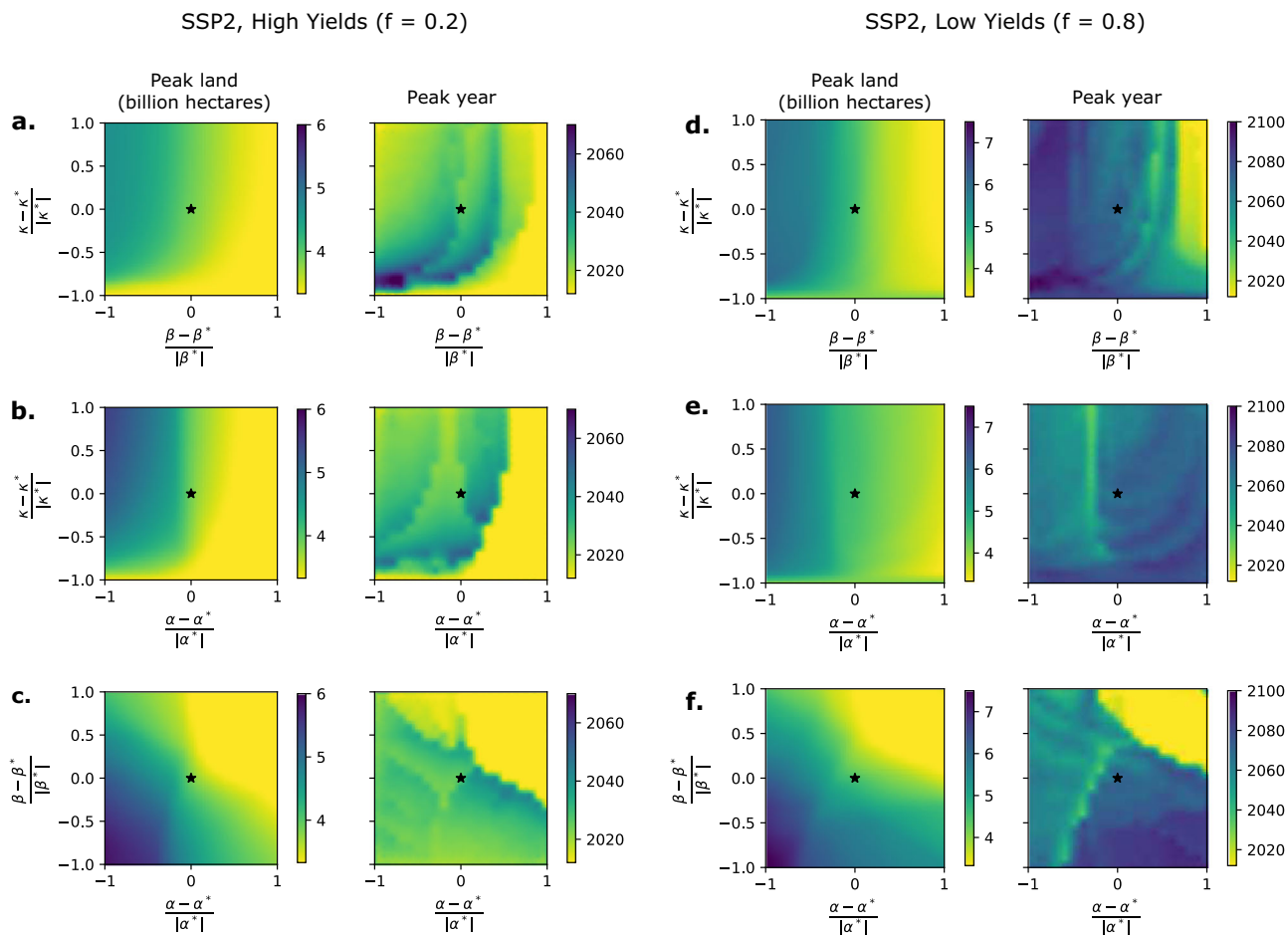
**Fig. 3** Baseline country-level projections when aggregated into five continental groups reveal distinct behavioral patterns of consumption. Country-level projections for global land-use change with respect to 2013 and corresponding eco-conscious consumer proportion till 2100 are aggregated into five continental groups. We use five continent groups to classify the 153 countries in our projection analysis (see Supplementary Data 1). Results are shown for yield scenarios ranging from high ( $f = 0.2$ ) to low ( $f = 0.8$ ) future yields at the SSP2 income and population scenario. Projections for the regional breakdown of global land-use change are shown in panel (a). Projections for corresponding eco-conscious consumer proportions in respective regions are shown in panel (b). For regional projections under all SSP scenarios at high ( $f = 0.2$ ) and low ( $f = 0.8$ ) future yields scenarios, see Supplementary Fig. 11.

scenario. This also causes the peak to occur several decades earlier. This occurs because more negative values of  $\alpha_i$  and  $\beta_i$  support land-intensive diets, and in countries with a high social learning rate, the population quickly learns to imitate a land-intensive diet, causing a spike in global land use. Below baseline values, increasing the social learning rate also causes the peak year to occur earlier, for most parameter values. Hence, social learning can only support eco-conscious diets if the underlying incentives work in the right direction. In this vein, there are a few regions of the parameter planes for the high yield scenario above baseline values for  $\kappa_i$  and  $\beta_i$  where increasing the social learning rate delays the year of peak global land use by several decades without causing an increase in the peak land use. This represents a noteworthy benefit (Fig. 4a, b).

To meet sustainability goals, an optimal outcome is to reduce peak global land use while simultaneously delaying the peak to a later year. This is especially true for the low yield scenario, where peak global land use is high. Achieving these two outcomes simultaneously through variations from the baseline parameters

can be difficult. However, there is a narrow band of values in the low yield scenario where  $\alpha_i$  and  $\beta_i$  are slightly above their baseline values, where peak land use is reduced without consequentially impacting the peak year (Fig. 4f). Since our baseline values represent the status quo, this suggests that modest improvements in incentives to adopt an eco-conscious diet could generate large benefits in land use, especially in a worst-case scenario where future yields are small.

Although changes in the non-income ( $\alpha_i$ ) and income ( $\beta_i$ ) net benefits of an eco-conscious diet have symmetric effects on peak land use, there is an asymmetry in their effects on the peak year (provided social learning rate remains at the baseline level, Fig. 4c, f). This asymmetry is even more stark when global populations are very high and global incomes are low (example: the SSP3 scenario in Supplementary Fig. 10). As a result, it is optimal that both income and non-income net benefits are increased simultaneously for maximum effect (in terms of peak land and also peak year). If only one of them can be increased from the baseline level, increasing non-income net benefits works better



**Fig. 4** Model projections with parameters deviated from the baseline setting highlight the impact of consumptional behavior and socio-economic factors on global land-use trajectories till 2100. Model projections of peak global land use and corresponding peak year are shown for parameters deviated from the baseline setting. Results are shown for the population and income scenario of SSP2 at the yield scenarios of  $f = 0.2$  (panels **a–c**) and  $f = 0.8$  (panels **d–f**). For comparison across SSP scenarios see Supplementary Fig. 10. For each contour plot, we vary two out of three parameters from their baseline setting while keeping the third fixed at the baseline setting. In panels **a, d**, we vary  $\kappa_i$  (social learning rate) and  $\beta_i$  (income net benefits of the eco-conscious diet) from the baseline values while keeping the values of  $\alpha_i$  (non-income benefits of the eco-conscious diet) fixed at the baseline level. For panels **b, e**, the parameter values of  $\beta_i$  are kept constant at the baseline level. In panels **c, f**, the parameter values of  $\kappa_i$  are kept constant at the baseline level while the other two remaining parameters are varied. The values of parameters are changed within  $-100\%$  to  $100\%$  of their baseline value. The variables  $\kappa^*$ ,  $\alpha^*$ , and  $\beta^*$  represent the baseline parameter values for the countries as estimated from the parameter estimation process. During projections, equivalent change is made to the baseline parameters of all countries. The black star in each contour plot represents the baseline setting. Peak year is defined as the year in which peak global land use is achieved during the projection.

than increase income-related net benefits, as this guarantees a delayed peak (see Fig. 4f).

## Discussion

Our work shows that coupled social-and-land processes can have large impacts on land use projections, ranging in the giga-hectares, and therefore should be incorporated in global land-use modeling, along with other more established factors such as economic forces and the impacts of climate change. Individual diets are influenced by complex social factors such as religion, concern for health, urbanization, female participation in labor, food prices, and sustainability practices<sup>43–46</sup>. Here, we focused on the effect of ballooning global land use as a stimulus for individuals to adopt more eco-conscious diets, against a backdrop where rising incomes also permit individuals to opt for land-intensive diets. We subsumed other factors in decision-making into our phenomenological parameters at the social ( $\kappa_i$ ,  $\beta_i$ ) and individual ( $\alpha_i$ ) levels that we inferred from the data.

We showed how coupled social-and-land dynamics can have giga-hectare impacts on land use, especially when future yield is low and/or population size is high, and we explored changes to social parameters that minimize peak land use and peak year under various scenarios for socio-economic development pathways and future agricultural yield. We found that increasing the net benefits (income and non-income) of adopting eco-conscious diets is an important way to reduce peak global land use. Reducing social learning rates holds the potential to accentuate the mitigating effect of increasing the net benefits (income and non-income) of adopting an eco-conscious diet (a simultaneous effect shows a reduction of 2 billion hectares in peak global land use). Reducing social learning can be vital if future benefits to adopting an eco-conscious diet decrease from their current baseline setting.

Many coupled human-and-natural models exhibit important social dilemmas, such as the Prisoner's Dilemma<sup>33,37,47</sup>. These dilemmas capture the clash between what is socially (i.e., Pareto) optimal, and what is in the best interest of individuals.<sup>48</sup> For instance, in the context of our model, eco-conscious dietary

consumers may be interpreted as “cooperators” while land-intensive dietary consumers may be interpreted as “defectors” who prevent the population from attaining socially optimal targets. This aspect of dietary decision-making deserves further thought and analysis, although we caution that any such analysis must also take into account the fact of global inequities.

Over-fitting is a concern when attempting to infer too many model parameter values from limited data, and this is a potential risk for the current model, given the limited availability of social data for inferring parameters of a coupled social-and-land use model. This suggests a need to collect global data on social aspects of dietary choices in a consistent way, to inform global land-use projections. Using survey instruments may be cost-prohibitive for such a project, but digital data is cheap and may provide a way to infer useful information about dietary social processes and decision-making from observational analyses<sup>49</sup>.

As a result of the over-fitting risk, we opted for a minimal model. However, its simplifying assumptions could impact its land-use projections. For instance, we did not include aquatic sources of food, we ignored the influence of institutions, and we assumed a simple binary classification of dietary behavior. A future extension of our model could include aspects of population heterogeneity such as a continuous behavioral spectrum along with age and gender structure. Future work could also explore the effects of social norms in order to determine how social inertia can accelerate or decelerate behavioral changes, as well as social learning between countries. For the purpose of simplicity in working with country-level data, we also assumed homogeneous behavior within each country by assigning unique parameter values to every country, and this could be relaxed in future research. Similarly, given the enormous greenhouse gas impacts of livestock<sup>50</sup>, a future social process model would take into account the perceived risk of climate change in modeling the behavioral drivers of a population.

Our model does not explicitly address certain key effects like the effect of changing yields (and other macroeconomic factors) on food prices<sup>51</sup> and thus, on dietary behavior. For instance, increasing productivity can increase food supply and thus reduce food prices. This can have a large effect on real income (purchasing power) in low-income countries, where a sizeable proportion of income is spent on food. Furthermore, a higher yield can cause the Jevons Paradox whereby higher productivity results in profitability leading to an expansion of agricultural area<sup>52</sup>. As our behavioral model only accounts for differences in utilities between the EAT-Lancet diet and an alternate diet, a weak assumption stating that changing yields symmetrically affect prices across all food groups can address the aforementioned issue in our model. In future work, such effects could be modeled by making the parameter  $\beta_i$  a function of the yield parameter  $f$ . We also note that our projections of reduced global land use due to a growth in eco-conscious dietary choices does not necessarily translate into reduced pressure on natural land states, since the land that becomes available due to less land-intensive diets could still be used for other forms of natural resource extraction such as forestry or mining. Finally, our assumption that populations adjust their dietary behavior in response to global land use for agriculture is a crucial assumption. Although this has support in some studies<sup>27,28</sup>, this trait could also be culturally contingent and therefore this assumption deserves further investigation. For example, some populations may be more sensitive to their local or national land use, than global land use.

Future research in coupled social-and-land use models can incorporate increasing sophistication to deepen our understanding of social processes around dietary choices and land-use dynamics, as well as their interaction with other socio-economic factors and other environmental dynamics such as climate

change. These models could inform land-use projections and deepen our insights into relevant processes, by incorporating the driving mechanisms behind our dietary choices and accounting for how they respond to changes in land use and socio-economic variables.

## Methods

**Coupled social-and-land use model.** The proportion of the population of country  $i$  living below the poverty line is denoted  $p_i$ . This proportion consumes a sustenance diet requiring  $c_i^S(t)$  hectares of global land per capita in country  $i$  in year  $t$ . The population above the poverty line in country  $i$  consumes, on average a diet that requires  $c_i^A(t)$  hectares per capita land globally in year  $t$  for its support. If the population of country  $i$  at year  $t$  is denoted by  $p_i(t)$  then the total land use due to dietary behavior is

$$L_i(t) = (c_i^S(t)p_i(t) + c_i^A(t)(1 - p_i(t)))p_i(t) \quad (2)$$

We divide the portion of the population above the poverty line (those responsible for using  $c_i^A(t)$  hectares per capita per year for their diet) into those eating an eco-conscious diet, and those eating a land-intensive diet (these will be defined in the following paragraphs). We model the time evolution of the proportion  $x_i(t)$  of individuals consuming an eco-conscious diet using the replicator dynamics of evolutionary game theory<sup>53</sup>. This requires specifying a net utility gain (or loss)  $\Delta e_i(t)$  for an individual to switch from a land-intensive diet to an eco-conscious diet (defining a fitness difference between two consumptional behavior)

$$\Delta e_i(t) = \beta_{0,i}m_i(t) + \alpha_{0,i} + \gamma_{0,i}L_i^G(t) \quad (3)$$

where  $m_i(t)$  is the average per capita income of the country  $i$  in year  $t$ , and where  $\kappa_i = \kappa_{0,i}\gamma_{0,i}$ ,  $\beta_i = \beta_{0,i}\gamma_{0,i}$ ,  $\alpha_i = \alpha_{0,i}\gamma_{0,i}$ , and  $\kappa_i$ ,  $\beta_i$ , and  $\alpha_i$  are as defined in the main text.  $L_i^G(t) = \sum_j L_j(t)$  is global land use due to dietary consumption. The replicator dynamics for  $x_i(t)$  are given as

$$\frac{dx_i}{dt} = \kappa_{0,i}x_i(1 - x_i)\Delta e_i(t) = \kappa_i x_i(1 - x_i)(\beta_i m_i(t) + \alpha_i + L_i^G(t)) \quad (4)$$

We note the remaining proportion  $1 - x_i(t)$  consume a land-intensive diet. The parameter  $\kappa_i$  is called the social learning rate. It determines whether any utility difference between two dietary behavior would lead to an effective rate of change in the composition of behavior in the population. It varies between 0 and 1. At  $\kappa_i = 0$ , there will be no change in the proportion of population above-poverty consuming an eco-conscious diet even when there is a nonzero utility difference between the two consumption behaviors.

We define an eco-conscious diet as one that requires an amount of land that is greater than the sustenance diet  $c_i^S$  but less than or equal to the eco-conscious EAT Lancet diet, which we denote  $c_i^E$  (and we note that  $0 < c_i^S < c_i^E$  always)<sup>40</sup>. Similarly, we define a land-intensive diet as one that requires more than  $c_i^E$  hectares of land, per capita (see Supplementary Fig. 13a). As mentioned above, we denote the average per capita land use due to eco-conscious and land-intensive diets in a country by  $c_i^A(t)$ . This quantity is inferred during the model fitting procedure from the assumption that

$$x_i(t) = 1 - e^{-c_i^E(t)/c_i^A(t)} \Rightarrow c_i^A(t) = -c_i^E(t)/\ln(1 - x_i(t)) \quad (5)$$

The dependence of  $x_i$  on  $c_i^A$  is shown in Supplementary Fig. 13b. We note that when  $c_i^A > c_i^E$  and it increases upwards towards  $\infty$ , the proportion of people above the poverty line that consume an eco-conscious diet (between the sustenance and the EAT-Lancet diet) decreases toward 0. When  $c_i^A < c_i^E$  and decreases toward  $c_i^S$ , the proportion of population with an eco-conscious diet increases. This description allows us to define eco-conscious consumption with respect to a reference point  $c_i^E$  (per capita consumption at the EAT-Lancet diet). The proportion of eco-conscious consumption goes from 1 to 0 monotonically as average per capita consumption of the above-poverty population goes from  $c_i^S$  to  $\infty$ . The EAT-Lancet diet can be found summarized in Supplementary Table 2.

We use the above equations to estimate  $\kappa_i$ ,  $\alpha_i$  and  $\beta_i$  by fitting the model output of  $L_i(t)$  (Eq. (2)) to the empirical data for  $L_i(t)$ . The empirical data are calculated using “Methods” from a previously published work<sup>2</sup>. The value of  $c_i^A$  is inferred from the values of  $x_i$  (which is generated during the fitting) and  $c_i^E$  using Eq. (5). We note that the value of  $c_i^A$  is also used to estimate global land use due to consumption by  $i$  at  $t$  using Eq. (2). During the fitting for each  $i$ , the time series for  $p_i$ ,  $P_i$ ,  $c_i^S$ ,  $c_i^E$ , and  $m_i$  are available. For more details see Supplementary Methods.

For the purpose of fitting the model to data and making projections, we also normalize  $L_i^G$  and  $m_i$  to ensure the inferred parameters have the same order of magnitude for all countries. More details about the normalization and the parameter estimation method can be found in Supplementary Methods.  $\kappa_i$  is a real number in the interval  $[0, 1]$  while the parameters  $\beta_i$  and  $\alpha_i$  are real numbers in the interval  $[-1, 1]$ . The estimated baseline parameters can be found included in the Supplementary Data 1 and Supplementary Figs. 3–5.

**Definition of land use: data and methods.** We use the model developed in a previously published work<sup>2</sup> to generate the country-level time series data of average



per capita land use between 1961 and 2013. The model is described briefly in Supplementary Information (under Supplementary Methods). The UN FAO-STAT (Food and Agriculture Organization<sup>1</sup>) data-set also provides country-level data for land used on agriculture and pasture land. However, this is not the same as our definition of ‘land use by *i*’. This is because countries are not entirely self-dependent in providing for their food demand. Consume in *i* can be partly produced in *j* and vice versa. Since the aforementioned model<sup>2</sup> accounts for differential yields of food sources, the data for per capita land use accounts for land used from across the globe to provide for the consumption in *i*. If two countries have similar dietary consumption, the country which has a lower effective yield has a higher value of per capita consumption than the country which has a higher value of effective yield.

In all our projections and analysis, we consider the land that is required to generate the food that ends up being consumed by humans. The land equivalent of food wastage is not considered in our calculations. The data reported by UN FAOSTAT’s land statistics division<sup>54</sup> accounts for land used for all agricultural purposes. This includes the land equivalent of food wastage. In Supplementary Fig. 1, we see the quantitative difference between their time-series and our global model output. The UN FAOSTAT estimated that 1.4 billion hectares were lost due to food wastage in the year 2007<sup>55</sup>. This number matches exactly with the difference between the two series at 2007 in Supplementary Fig. 1.

**Model projections.** We include 153 countries to general country-level, continental, and global projections to 2100. We refer to simulations using the fitted values of  $\kappa_i$ ,  $\alpha_i$ , and  $\beta_i$  as the baseline projection or the baseline scenario. For the parameter plane analysis (Fig. 4, we conduct projections across a range of parameter values above and below the baseline values. Each projection is conducted under a scenario (for more details see Methods on Population, income and yield scenarios below). Land used for dietary purposes,  $L_i(t)$ , are projected using

$$\begin{aligned} \frac{dx_i}{dt} &= \kappa_i x_i (1 - x_i) (\beta_i m_i(t) + \alpha_i + L_i^G(t)) \\ L_i(t) &= (p_i(t) c_i^S(t) + (1 - p_i(t)) c_i^A(t)) P_i(t) \\ L_i^G(t) &= \sum_i L_i \end{aligned} \tag{6}$$

where the variables  $m_i(t)$  and  $L_i^G(t)$  are normalized income for *i* at *t* and normalized global land use at *t* (normalized with respect to highest income achieved and global land use at 2013, respectively). Where,  $c_i^A(t)$  is evaluated as follows during the projection

$$c_i^A(t) = \begin{cases} -\frac{c_i^U(t)}{\log_e(1-x)} & \text{if } c_i^S(t) < -\frac{c_i^U(t)}{\log_e(1-x)} < c_i^{U,\max}(t) \\ c_i^{U,\max}(t) & \text{if } -\frac{c_i^U(t)}{\log_e(1-x)} \geq c_i^{U,\max}(t) \\ c_i^S(t) & \text{if } -\frac{c_i^U(t)}{\log_e(1-x)} \leq c_i^S(t) \end{cases} \tag{7}$$

Population and income projections to 2100 are taken from the SSP scenarios (see below in ‘‘Methods’’). The per capita consumption curves ( $c^{U,\max}$ ,  $c^S$ , and  $c^L$ ) are extrapolated based on the scenarios for *f*, which controls yield. For every scenario of projection, we project poverty levels to linearly change based on their historic trend. If poverty levels reach 0 after a linear decrease during projection, it stays at 0. During projection, we used the normalized version (Eq. (6)) of the (Eq. (4)). For more details on this normalization see Supplementary Methods.

**Method for calculating  $c_i^L(t)$ ,  $c_i^{U,\max}(t)$ , and  $c_i^S(t)$ .** The upper bound of per capita consumption,  $c^{U,\max}$ , is calculated by assuming that diets that cause the high land use impact are the one that allow a very high intake of items that belong in the meats and dairy diet groups. Similarly, for  $c^S$ , we assume that the sustenance diet is the one that allows the least consumption of items in those groups. To calculate the per-capita land use for the EAT-Lancet diet,  $c_i^L(t)$ , we take the EAT-Lancet diet introduced in ref. <sup>40</sup>. The values for  $c^{U,\max}$ ,  $c^S$ , and  $c^L$  can be calculated between 1961 and 2013 for countries whose data is reported in FAOSTAT’s food balance sheets<sup>1</sup>.

We categorize each of the 21 food items listed in the food balance sheets into one of the seven groups of diet—fruits, vegetables, grains, meats, dairy, oils, and sugar. For every country *i*, we calculate its maximum possible land impact diet by replacing its average consumption of items in the ‘‘meats’’ and ‘‘dairy’’ groups (in kcal capita<sup>-1</sup> day<sup>-1</sup>) with the consumption values of the countries that consumed the most of those items that year. Similarly, for the sustenance diet, we replace them with the consumption values of countries that consumed the least of those items in that year. Values for the remainder of the diet (i.e., the other groups—fruits, vegetables, grains, sugar, and oils), remain the same as reported data. An example of such a construction is shown in Supplementary Table 1). The method of evaluating these bounds is explained in more detail in Supplementary Methods. For the Lancet diet, we map the available diet in the original paper<sup>40</sup> to food subgroups in our construction (see Supplementary Table 2).

Once these hypothetical diets (maximum, sustenance, and EAT-Lancet) are constructed for a country *i*, we use a previously published model<sup>2</sup> to calculate the total land required to generate that per capita dietary demand for the population of *i* in *t* (see Supplementary Methods for an overview of this model). We divide the output of the model with the population of *i* at that year to obtain per capita land use equivalent

of the hypothetical diet ( $c^{U,\max}$  if maximum land impact diet,  $c^S$  if sustenance diet and  $c^L$  if EAT-Lancet diet). A sample result of this method is shown in Supplementary Fig. 12. The time series for  $c^S$ ,  $c^L$ , and  $c^{U,\max}$  are shown for six sample countries.

In order to evaluate these values for years beyond 2013 (for purpose of projections), we use an extrapolating parametric function (see ‘‘Method’’ section for *f* scenarios).

**Population, income, and *f* (yield) scenarios.** We use the datasets available from the SSP scenarios<sup>41</sup> for projecting population and income to 2100. A number of existing models are compiled in the SSP Public Database hosted by the International Institute for Applied System Analysis (IIASA). Among them, we choose the OECD Env-Growth Model<sup>42</sup> for obtaining future projected values of country-level population and income. In Supplementary Methods, we discuss the inclusion procedure of countries in our analysis. There we provide reasons for the exclusion of certain countries from the analysis. The choice for OECD Env-Growth was made because it covers projections for the maximum number of countries among the existing models.

The bounds for land required to support the maximum diet, the sustenance diet, and the EAT-Lancet diet ( $c^{U,\max}$ ,  $c^S$ , and  $c^L$ ) are projected into the future with a parametric function. The parameter *f*, a number between 0 and 1, represents scenarios of yield future. We now explain the meaning of a yield scenario parameterized by *f*. If the trend of  $c^{U,\max}$ ,  $c^S$ , and  $c^L$  between 1990 to 2013 is decreasing (which is more often than increasing), the series can at least reach *f* times its 2013 value in the future. Similarly, if the trend is increasing, it can reach at most  $1 + f$  times its 2013 value in the future. The rate at which a projected curve (either  $c^{U,\max}$ ,  $c^S$ , or  $c^L$ ) reaches towards its bound is determined by its rate between 1990 and 2013.

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

$$c(t) = \begin{cases} c(2013) - (c(2013) - c(2013)f)(1 - e^{-\beta(t-2013)}), & \text{if initial trend is decreasing} \\ c(2013) + (c(2013)f)(1 - e^{-\beta(t-2013)}), & \text{if initial trend is increasing} \end{cases} \tag{8}$$

Here, *f* is the tune-able parameter—a real number between 0 and 1 that defines the future yield scenario. For the above equation, *t* is always greater than 2013. The exponent  $\beta_i$  is adjusted such that continuity is maintained at 2013 between the initial trend,  $ae^{bx}$ , and the projected trend *c*(*t*). The continuity condition assures that the time series of  $c^{U,\max}$ ,  $c^L$ , and  $c^S$  do not abruptly change in 2013 thus assuring that abrupt changes in  $x_i(t)$  do not occur in 2013. That is

$$\beta = \begin{cases} -\frac{1}{c(2013)} \frac{abc^{2013b}}{1-f}, & b < 0 \\ \frac{abc^{2013b}}{c(2013)f}, & b > 0 \end{cases} \tag{9}$$

In Supplementary Fig. 6, we show two examples of  $c^{U,\max}$ ,  $c^S$ , and  $c^L$  projection till 2100 using the above method. The two countries that are chosen as examples are the USA and Netherlands.

If we assume that the maximum land impact diet, sustenance diet, and the EAT-Lancet diet for countries remain constant from 2013 onward (in kcal capita<sup>-1</sup> day<sup>-1</sup>), *f* scenarios represent scenarios of yield future. Then, a low *f* value represents improvement towards high yield values. A high *f* value represents the deceleration of yield rates, causing them to converge to inferior future values.

### Data availability

This study uses a series of publicly available datasets as inputs for the coupled social and land-use model.

The data for country-level poverty was available from The World Bank: Shared Prosperity: Monitoring Inclusive Growth: <https://www.worldbank.org/en/topic/poverty/brief/global-database-of-shared-prosperity>.

The data for country-level population and income projections till 2100 under multiple SSP scenarios were available from the publicly available SSP database hosted by the International Institute for Applied Systems Analysis: <https://tntcat.iiasa.ac.at/SspDb>.

The country-level per-capita income (GDP PPP per capita) data used for fitting the model was available from the public database of The World Bank: <https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD>.

The time series country-level food consumption data were available from a publicly accessible database of the Food and Agricultural Organization of the United Nations, the FAOSTAT: <http://www.fao.org/faostat>.

All the necessary datasets mentioned here can also be found in the publicly accessible Github repository: <https://github.com/Saptarshi07/Coupled-Social-and-Land-Dynamics>.

### Code availability

The python scripts for (i) the parametrization of the model and (ii) land-use projections using the parameterized model can be found in the following public Github repository: <https://github.com/Saptarshi07/Coupled-Social-and-Land-Dynamics>.

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## Author contributions

All authors conceived of and designed the study. S.P., C.T.B., and M.A. developed the theoretical model. S.P. performed the analysis, produced the results, and wrote the first draft. All authors revised and commented on the paper equally.

## Competing interests

The authors declare no competing interests.

**Additional information**

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