Societal dynamics of low-carbon lifestyles

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Abstract

Lifestyle change is considered an important demand-side measure for climate change mitigation. To understand the relationships of low-carbon lifestyles with the global environmental and socioeconomic dynamics, and the main drivers of such lifestyles, there is a growing need for modelling studies that combine societal transformation with the integrated assessment of climate, environment and economy. This paper presents an exemplary modeling study that extends an integrated assessment model with psycho-social mechanisms to explore societal dynamics. Based on the findings of this modelling study, the paper then discusses the potential contribution of system dynamics modelling to investigate the societal dynamics and drivers of low-carbon lifestyles.

1. Introduction

Lifestyle change is considered an important demand-side measure for climate change mitigation. Lowering energy demand with climate-friendly lifestyle choices could be the key to achieving 1.5°C pathways[1]. Similarly, shifting towards plant-based diets and reducing food waste can considerably lower the agriculture and land-use emissions, and contribute to keeping the global food system within planetary boundaries[2, 3, 4]. Building upon this growing scientific evidence, recent IPCC reports have underlined the importance of lifestyle change to reduce anthropogenic emissions, increase the carbon sink in land and reach the 1.5°C target[5, 6]. Lifestyle change can also contribute to the achievement of multiple sustainable development goals (SDGs). For instance, a low energy demand also implies global decent living standards and decreased poverty (#1), low air pollution and better human health (#3), responsible consumption and production (#12), and less ocean acidification (#14)[1]. Moreover, lifestyle change, e.g. sustainable diets, reduces the intensity of trade-offs between the SDGs on hunger, sustainable agricultural production and biodiversity[7].

The mitigation potential of lifestyle change is assessed either with a top-down perspective in quantitative scenario studies that mostly use integrated assessment models of energy, economy and environment. This model-based approach to understand lifestyle change is facing multiple challenges. Existing top-down scenario studies are based on stylized assumptions for demand, which do not necessarily imply a feasible rate of societal change and may not lead to a realistic mitigation potential of lifestyle change. For instance, a recent study[4] shows that if the world's average diet is flexitarian by 2050, meaning that the average red meat consumption is equivalent to one serving per week and constituting 0.5% of daily calories, agricultural GHG emissions would be reduced by around 50%. Currently, 1.8% of daily calories are obtained from red meat in the world's average diet[8]. The difference is small, but it would require billions of consumers to change their diets. Therefore, stylized demand assumptions do not necessarily imply a *feasible rate of societal change* and may not lead to a realistic mitigation potential of lifestyle change.

Furthermore, in the existing integrated models, human systems are not explicitly modeled. For instance, the feedback between physical systems (e.g. climate) and human systems (e.g. emission response) is not considered. A recent study[9] shows that the uncertainty posed by human emission behavior in relation to physical systems is similar in magnitude to the physical uncertainty of global temperature change. To navigate this wide uncertainty range posed by human behavior, a wider variety of scenarios is needed, considering the behavioral factors and the feedbacks between the human and physical systems.

Overcoming these challenges requires bridging the bottom-up empirical studies on the drivers of lifestyle change with top-down integrated assessments. Dynamic simulation modelling can facilitate this linkage by synthesizing the available empirical data and theoretical conceptualization, by scaling up and generalizing the context-specific lifestyle change, and by generating feasible and plausible scenarios of societal change towards low-carbon lifestyles.

As a prominent dynamic simulation methodology, system dynamics can especially be useful due to its strength and explanatory capacity in studying macro feedback structures of social, environmental and economic dynamics. The feedback perspective of system dynamics can help to capture the feedback loops as the sources of nonlinearity related to individual and social behavior not only within human systems, but also between the human and natural systems. Furthermore, the top-down modelling approach in system dynamics represents the social and demographic heterogeneity in population compartments. This segmentation approach coincides with the structure of big data and the effect of digitalization on decision-making. In other words, with increasing digital footprint of individuals and corporate or governmental mining of this big data, demographic and social profiling is becoming the basis of socioeconomic decision-making. In an age where digitalization creates distinct population segmentation and provides large-scale data for modelling studies, the heterogeneity of societal change towards low-carbon lifestyles can adequately be captured by compartmental system dynamics models.

The objective of this paper is to demonstrate how system dynamics modelling can be used to investigate the societal dynamics and key drivers of transition towards low-carbon lifestyles. For this purpose, we employ a recently published case study on dietary change[10]. Based on this case study, we describe a system dynamics model of behavioral change towards sustainable diets based on individual and societal factors. We echo the findings of this case study to demonstrate how such a model can be used to explore population dynamics and to identify the key drivers of societal change even in the absence of large scale data.

In the remainder of this paper, Section 2 introduces the case of dietary changes, describes the conceptual basis of the model, and explains the computational methods used to identify the key drivers. Section 3 presents the simulation and analysis results, while Section 4 discusses the generalizability of this modelling approach for other lifestyle domains and its limitations.

2. Methods

2.1 Dietary change

The food system is responsible for 24% of global annual greenhouse gas emissions (together with land use)[11], with crop and livestock production being the dominant sources of these emissions. The food system also causes vast environmental degradation in terms of freshwater use, deforestation, biodiversity loss and ocean acidification[12, 13]. Several studies, such as the recent EAT-Lancet report on planetary diets[14], have demonstrated that sustainable and plant-based diets may substantially mitigate these adverse effects[4, 7], while contributing to public health as well[3, 15]. Therefore, lifestyle change in the nutrition domain, i.e. shifts towards plant-based diets, has a high potential to tackle multiple challenges.

2.2 Modelling dietary change dynamics[1]

This study investigates the factors that steer diet changes towards low meat consumption by linking a model of human behavior to an existing integrated assessment model. In particular, we extended the FeliX model[16, 17, 18] with population segmentation for dietary choices, and we modelled the shifts between these segments based on main psychological theories that are used to explain individuals' environmental actions.

To conceptualize diet shift dynamics we considered two main feedback mechanisms (Fig. 1) based on two complementary theories of psychology. According to the Theory of Planned Behavior[19], behavioral intentions are formed by perceived behavioral control or self-efficacy, subjective social norms, and attitude, which basically refers to whether the suggested behavior is evaluated positively or not. Diet change due to social norms forms a positive feedback loop, since a higher number of vegetarians shifts the norm, which further stimulates diet change behavior. According to the Protection Motivation Theory[20], actions are determined by threat appraisal, an individual assessment of the severity of a threat, and coping appraisal – the extent to which an individual can, and is willing to, cope with the threat. This theory has been used to model emission behavior[9] by linking threat appraisal to climate events.

In the context of diet change, combined with the global food system represented in the FeliX model, threat appraisal of climate change risk forms a negative feedback loop, where the diet shift to vegetarianism leads to lower emissions, fewer climate events, and a lower threat. Public risk perception is argued to depend on various factors such as social values, media coverage, self-interest and the direct observation of risk, rather than purely quantitative risk metrics[21]. Following previous modelling studies[9], we assume that climate events observed and retained in public memory represent the perceived climate risk, since they refer to direct public experiences and media coverage.

Health risks attributed to high red meat consumption is another important concern that motivates people to change their diets[22]. The health benefits of sustainable diets have been widely discussed[3, 23, 24, 25], and a healthy and sustainable diet is quantitatively defined based on an integrated framework that combines health effects and the planetary boundaries of the food

[1] This section is published earlier in Eker et al. (2019)[10].

system[14]. Sustainable diets, such as a flexitarian diet with one serving of red meat per week, are concluded to have the potential to reduce deaths by 10.8-11.6 million per year[14]. Following this, we included health risk in the model as a driver of diet change behavior. We modelled perceived health risk endogenously in relation to average red meat consumption.

The model is formalized with a public segmentation and innovation diffusion approach[26, 27]. The population is divided into two – meat-based diet followers and vegetarians. The flows, that is, diet switches between the two groups are modelled according to income change, since increasing income leads to higher meat consumption, especially in developing countries[28], and the behavioral factors outlined in Fig. 1. Population heterogeneity is taken into account in terms of age, gender, and education level. The global food demand resulting from these population dynamics is reflected on the land use and climate modules of the FeliX model. Following Beckage et al.[9], randomly generated climate events driven by global temperature change are used to compute the perceived climate threat. (See **Appendix I** for a detailed model description.)

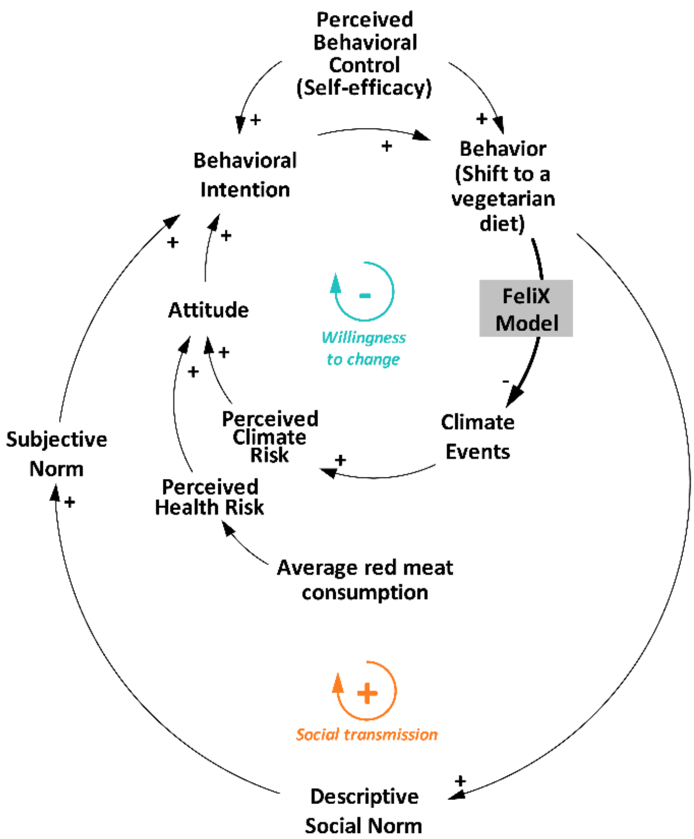


Fig. 1. Conceptual framework of the diet change model. The figure illustrates the behavioral framework underlying the diet change model. The arrows represent a causal relation between two factors, and the polarity of an arrow indicates whether the relation is positive or negative. Diet change behavior (action) is determined by behavioral intention, as well as by self-efficacy, response efficacy, and response cost. Intentions are formed by subjective norms – an individual's perceptions of the social norms and attitude towards diet change – whether it is perceived as good or bad. While social norms are affected by the spread of the behavior, thus forming the positive *social transmission* loop, attitudes are driven by the perceived threat of climate events, forming the negative *willingness to change* loop. Perceived health risk attributed to red meat consumption is another factor that affects attitude towards diet change.

Each population segment is associated with a reference diet composition to consider demand changes for different food categories. To add variety to diet compositions beyond a reference meat-based and a reference vegetarian diet, we consider four diet composition scenarios where each population segment (meat-eaters and vegetarians) was associated with a different diet type shown in Table 1. For instance, Scenario 3 assumes that all meat-eating population will be flexitarian by 2050; and all vegetarian population will actually be vegan by 2050. Behavioral factors such as self-efficacy or response efficacy can play different roles in these diet composition scenarios. For instance, self-efficacy for switching from meat-eating to a vegetarian diet may differ from switching to a vegan diet. However, to our knowledge, there is currently no information and data on these differences in the literature. Therefore, we quantify the behavioral factors equally in these four diet composition scenarios, yet consider potential differences among the four scenarios in the uncertainty analysis.

Table 1. Diet composition scenarios. The table shows the diet composition associated with the two population segments in four diet composition scenarios. In scenarios 1, 2, and 3 the diet composition is assumed to change gradually from the reference diet type in 2020 to the given diet type in 2050. The numbers in parentheses refer to the percentage of daily calories taken from animal products in each diet type.

Scenario	**Meat-eater's diet**	**Vegetarians' diet**
Sc0_Reference	Reference meat-based diet (17.2%)	Reference lacto-ovo vegetarian diet (9%)
Sc1_Healthy+Ref	Healthy eating guidelines by 2050 (14%)	Reference lacto-ovo vegetarian diet
Sc2_Healthy+Vegan	Healthy eating guidelines by 2050	Vegan diet by 2050 (0%)
Sc3_Flexitarian+Vegan	Flexitarian by 2050 (11.7%)	Vegan diet by 2050

2.3 Global Sensitivity Analysis and Sobol indices

Data availability for the extent and drivers of lifestyle change, or dietary change in particular, especially on a global scale is highly limited. Therefore, although the model is quantified according to empirical studies (See Appendix I), most psycho-social parameters are highly uncertain. To deal with these uncertainties, we use the model to generate a scenario ensemble that covers the implications of these uncertainties and to identify the factors that create the largest variance, hence most important for the dietary change dynamics. For this purpose, we employ Global Sensitivity Analysis (GSA)[29, 30], which is a multivariate sensitivity analysis method for evaluating the impact of uncertain inputs of complex environmental models.

GSA calculates the importance of each input in interaction with all other inputs. This makes it suitable for complex models that include a large number of highly uncertain inputs and their nonlinear relationships. As a computationally-intense GSA technique, variance-based Sobol indices represent the contribution of each uncertain model parameter to the output variance[31]. This study uses Sobol indices to identify the most influential uncertain inputs, because they indicate the sensitivity caused by a parameter regardless of the initial parameterization of the model.

GSA applications distinguish between the first-order and total Sobol indices[31]. The fraction of the total variance attributed only to an individual input factor X_i is the *first order Sobol sensitivity index* ($S_{1,i}$), whereas the fraction of variance attributed to an input factor and its interactions with all other factors is the *total Sobol sensitivity index* ($S_{T,i}$). Therefore, $S_{1,i}$

provides an isolated measure of sensitivity to the input factor X_i, and $S_{T,i}$ gives an account of the sensitivity to a parameter's overall role in the output. Equation 1 denotes $S_{1,i}$, where $V[Y]$ is the unconditional variance of model variable Y and V_i is the variance of the conditional mean of Y when the parameter X_i is fixed within its range. Similarly, Equation 2 denotes $S_{T,i}$, where $V_{\sim i}$ is the variance of the conditional mean of Y when all factors except X_i are fixed.

$$S_{1,i} = \frac{V_i}{V[Y]} = \frac{V\left[E\left(Y/X_i\right)\right]}{V[Y]} \quad (1)$$

$$S_{T,i} = \frac{V_{\sim i}}{V[Y]} = \frac{V[E(Y/X_{\sim i})]}{V[Y]} \quad (2)$$

Sobol indices are calculated using the Python SALib library[32] which implements a sampling design generated to compute the unconditional variance of the output based on Monte Carlo simulations[33]. This sampling method requires $N=n(2p+2)$ experiments, where n is the number of simulations and p is the number of uncertain inputs. For our model with 36 parameters, we reported the results of N=185,000 experiments.

3. Results

3.1 Reference simulations

The model is simulated with the reference calibration of psycho-social parameters (Appendix II) for the four diet composition scenarios listed in Table 1. Figure 2 and 3 show the results for the fraction of vegetarian diet followers, i.e. the fraction of vegetarian population segment, and the total global GHG emissions of the agriculture and land use sector, respectively. In all diet composition scenarios, the fraction of vegetarians decline from 2000 until around 2040, to approximately 17%. This decline is attributed to the effect of increasing income especially in developing countries. After 2040, the vegetarian population fraction increases only in the reference diet composition scenario, where the average meat consumption is highest. This is due to the increasing effect of health and climate risk which also triggers the reinforcing *social transmission* loop. In the other diet composition scenarios with relatively low average meat consumption, such positive effects on dietary shifts are not observed, therefore the vegetarian population remains relatively stable at 16%.

Figure 3 shows the reference simulation results for the total GHG emissions from the agriculture and land use for the four diet composition scenarios. As described earlier, Scenario *1, 2, and 3* assume a transition between 2020 and 2050 from the reference diet consumption of the meat-eater and vegetarian population segments to the given diet compositions, such as flexitarian or vegan. In *Sc0* with reference diet compositions, emissions keep increasing until ~2065 and up to ~16 GtonCO_2eq (from the historical value of 10.2 GtonCO_2eq in 2010). They decrease afterwards, attributed to dietary shifts in the population (Figure 2). In *Sc 1 and 2,* where the meat eaters (around 83% of the population) follow healthy-eating guidelines and vegetarians (around 17% of the population) follow the average vegetarian and vegan diet, respectively, emission dynamics are relatively stable around 12 GtonCO_2eq. Still, they demonstrate a decline until 2045 due to the diet composition transition, and slightly increase and decrease again in the following decades due to population increase, then switch to vegetarianism. The largest reduction in the emissions is observed in *Sc 3*, where the larger fraction of population (meat-eaters) follow a flexitarian diet, and vegetarians follow a vegan diet.

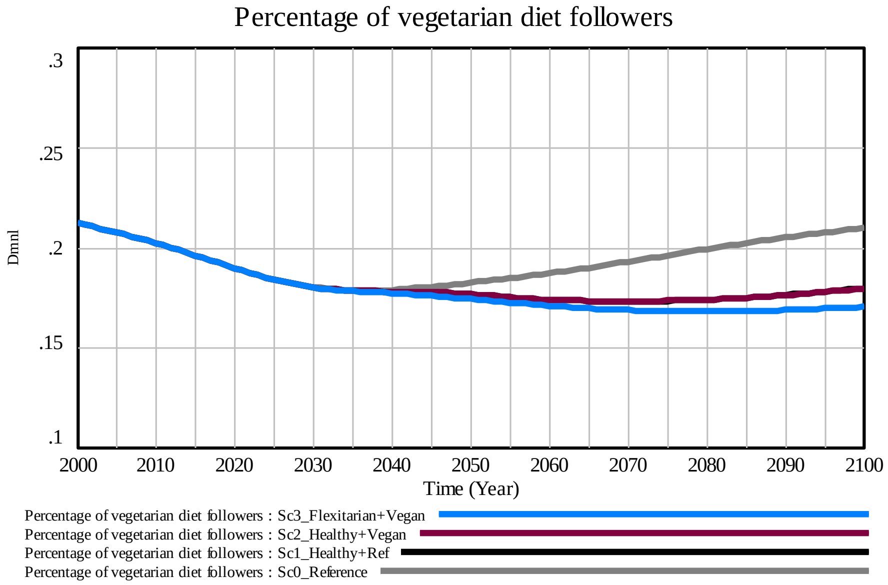


Figure 2: Reference simulation results for the percentage of vegetarian diet followers. The figure shows the simulation results for the 4 diet composition scenarios listed in Table 1 in the period 2000-2100. The fraction of vegetarian diet followers in the global population declines in all diet composition scenarios until around 2035. The grey line shows the model output for *Sc0* with the reference diet composition. The black line and the overlapping dark red line show *Sc1* and *Sc2*, respectively, corresponding to the combination of health eating guidelines for meat-eaters to the reference vegetarian and vegan diets for the vegetarian population. The blue line refers to *Sc3*, which is the combination of flexitarian and vegan diets for meat-eater and vegetarian population segments.

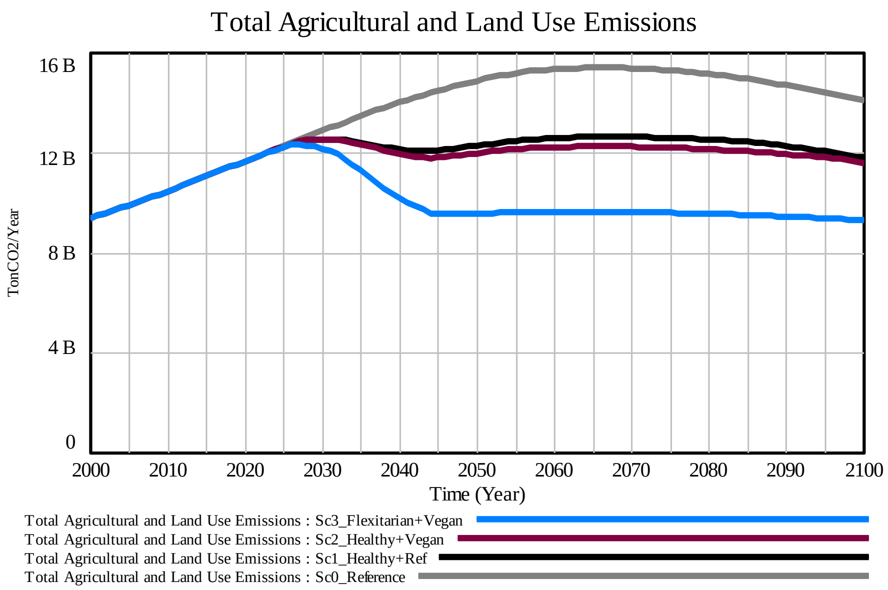
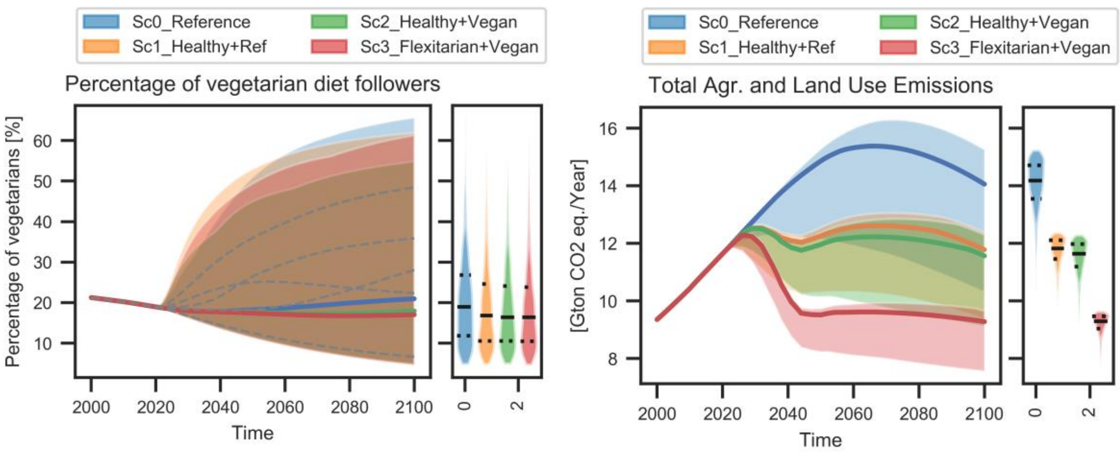


Figure 3: Reference simulation results for the total agricultural and land use emissions. The figure shows the simulation results for the 4 diet composition scenarios listed in Table 1 in the period 2000-2100. The grey line shows the model output for *Sc0* with the reference diet composition. The black line and the dark red line show *Sc1* and *Sc2*, respectively, corresponding to the combination of health eating guidelines for meat-eaters to the reference vegetarian and vegan diets for the vegetarian population. The blue line refers to *Sc3*, which is the combination of flexitarian and vegan diets for meat-eater and vegetarian population segments.

3.2 Environmental impact of diet change[2]

To account for the uncertainty in behavioral parameters, we simulate the model 10,000 times, each with a unique combination of the parameter values sampled from their uncertainty ranges (Appendix II). The dynamic simulation results show a wide range for the *Percentage of Vegetarians* in the total population especially towards 2100. It is however mostly around 20% (Fig. 4a). Both the reference simulation and the uncertainty space demonstrate a higher percentage of vegetarians in the reference diet composition scenario compared to the other diet composition scenarios. This result can be attributed to climate and health risk, which are higher in the reference diet composition scenario and stimulate more shifts to vegetarianism. GHG emissions from agriculture and land use also show a wide range of dynamics (Fig. 4b). In the reference diet composition scenario (Scenario 0), the emissions vary between 10 and 15 GtonCO$_2$eq in 2100. This implies that, despite increasing population and food demand, the emissions can be brought back to current values (10.2 GtonCO$_2$eq in 2010) by 2100, even with the current average compositions of meat-based and vegetarian diets, if a significant shift to vegetarianism occurs. Still, more significant emission savings are obtained in the low-meat diet composition scenarios.

These findings also show that diet composition has a bigger impact on the food system's environmental footprint compared to the extent of diet shifts triggered by behavioral factors. Even if up to 40% of the global population turns vegetarian, the environmental benefits of diet change may not be fully observed as long as the remaining meat-eaters consume the current averages. Therefore, instead of drastic shifts by a small group, population-wide changes are required, even though the extent of such changes is not maximal.



(a) ***(b)***

Figure 4: Dynamic simulation results for (a) the percentage of vegetarian diet followers in the total population, (b) total agricultural and land use emissions. The bold colored lines show the reference simulation results for each diet composition scenario, while the shaded area around them depict the uncertainty space generated by the behavioral parameters with ± 50% uncertainty around their reference values. The violin plots on the right-hand side of each plot show the density distribution of simulation results in 2100 with the 25th, 50th, and 75th percentiles marked. While the range of percentage vegetarian population is quite wide, the median value is below 20% in every diet composition scenario. Emissions from the agriculture and land use sector also show a wide variety with respect to the spread of vegetarianism and diet composition scenarios. Although there are a few cases where the increasing pattern of emissions

[2] This section is based on Eker et al. (2019).

is ceased even in the reference diet composition scenario, the highest reduction potential is in the third diet composition scenario.

3.3 Drivers of diet change behavior[3]

We use two complementary approaches to investigate the factors that could drive a widespread diet change. The first approach answers the question "Which behavioral factors cause the highest sensitivity in the vegetarian percentage of the global population?", whereas the second one addresses, "Which factors are associated with a high spread of vegetarians in the global population?"

First, we identify the model parameters that contribute most to the variance in model outcome in each diet composition scenario based on a Global Sensitivity Analysis and Sobol indices. According to the results for the reference diet composition scenario (Fig. 5), the parameter *x0 social norm* of the young population (ages 15-44) contributes most to the variance of model output. This parameter is the inflection point of the logistic function that defines the relationship between the descriptive social norm (percentage of vegetarians in each demographic group) and the diet change behavior (Figure A.2). In other words, it represents the spread of vegetarian diet where the slope of the logistic function that define the social norm effect is steepest, and consequently the feedback effect is strongest. This finding demonstrates that diet change behavior is influenced most by a high public responsiveness to initial changes in the vegetarian population. The difference between the first-order (S1) and total (ST) Sobol indices of *x0 social norm* indicates that its interaction with other model parameters causes more variation in the output. This can be attributed to the amplifying effect of social norms once the diet change attitude is set with health and climate risk perception.

The second most influential parameter is the *self-efficacy multiplier* of the females. Self-efficacy plays a dual role in diet change both on intention and action, and the self-efficacy of females is assumed to be higher than that of males. Therefore, this finding emphasizes the dual and conclusive role of self-efficacy once the attitude is set according to risk and social norms. The parameter in the third rank is *normal fraction intended to change diet.* This parameter represents the base fraction of meat-eaters who intend to switch to a vegetarian diet, without the effects of social norm, risk perception, self-efficacy, and response-efficacy. Both these parameters contribute more to the variance in interaction with other factors (ST).

The following parameters in the Sobol sensitivity ranking relate to how quickly the young population responds to health risks (*x0 health risk attitude*), the extent of responses by the young population to social norms (*L social norm*), and the response efficacy of secondary education graduates. In the socio-psychological modelling framework we use, the young population is already more inclined to diet change due to a higher susceptibility to social norms and a higher responsiveness to health risks. Therefore, the high sensitivity of the model to the parameters representing youth emphasizes the potential of using low hanging fruit as leverage points for diet change. Regarding the response efficacy, secondary education graduates constitute the largest demographic group according to educational attainment level. Therefore, a high sensitivity to this parameter highlights the importance of assuring this large demographic

[3] This section is adapted from Eker et al. (2019).

group about the positive impact of diet change. The factors related to climate risk perception (*L and x0 risk attitude*) are ranked after response efficacy in terms of their contribution to variance.

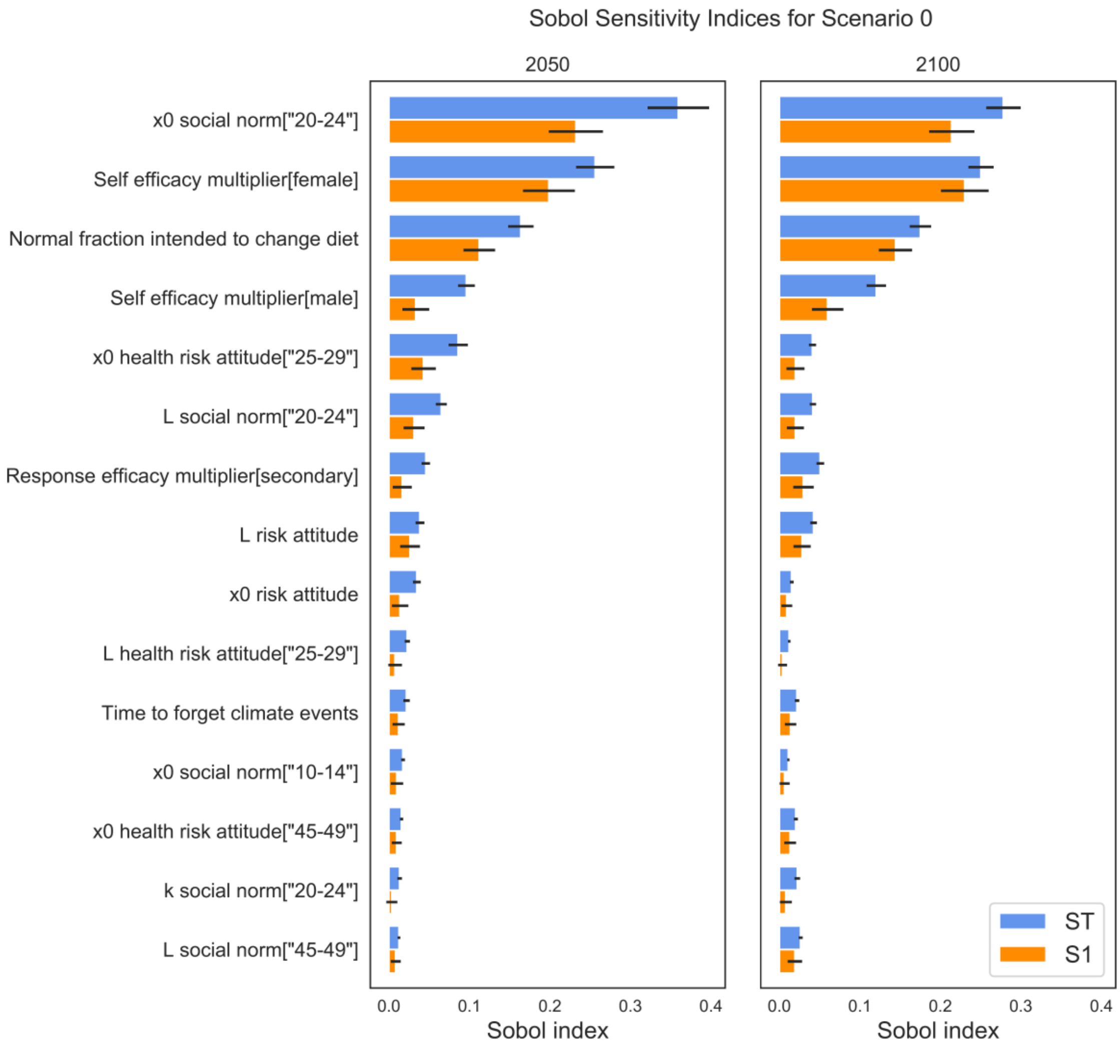


***Fig. 5. Sobol sensitivity indices for the Percentage of Vegetarians* in 2050 and 2100 for the reference diet composition scenario.** The figure shows the first-order (S1) and total (ST) Sobol indices of the model inputs, that is, the contribution to the variance of *Percentage of Vegetarians* in the model output. The higher the Sobol index, the larger the variance caused by an input. The model inputs with less than 1% contribution (Sobol index smaller than 0.01) are not displayed in this figure. First order Sobol indices (S1) refer to the individual contribution of a parameter to the output variance, whereas total Sobol indices (ST) refer to the contribution of a parameter to the output variance in interaction with all others. The difference between S1 and ST indicates the importance of parameter interactions. The whiskers show the 95% confidence interval. The parameter 'x0 social norm ["20-24"]' that defines the rapidness of the young population's response to social norms is the most influential, followed by female self-efficacy. The parameters in high ranks do not differ between 2050 and 2100. The definitions of the parameters can be found in Appendix II.

When the sensitivity indices are calculated in 2100, the top factors remain the same. However, the sensitivity indices of these top parameters, especially *x0 social norm*, decline and those of lower rank parameters, such as the ones related to climate risk perception (*L risk attitude*) and social norms among the middle-aged population (*L social norm [45-49]*), increase. Hence, contributions to the model output uncertainty from low-ranking factors do increase in the long-term. Furthermore, the difference between S1 and ST is tapered in the long-term when the diet shifts approach saturation (Fig. 4a), implying that parameter interactions are not as significant as before when compared to individual contributions to variance.

4. Conclusion and Discussion

This paper has demonstrated how system dynamics modelling can assist exploring the pathways of societal change towards low-carbon lifestyles. The modeling results showed that significant benefits for climate change mitigation would require substantial and widespread diet shifts. Such substantial shifts, for instance more than 40% vegetarian population, are observed in a few simulation cases with optimistic assumptions. Acknowledging the uncertainty in model parameterization due to lack of data, this study also identified the factors that contribute to the variance of diet shifts most. Within the specified modelling framework, social norms and self-efficacy create the highest sensitivity in diet shift behavior, while the parameters that represent health and climate risk perception are relatively less influential.

The results emphasized the importance of taking demographic heterogeneity into account, since the young population's response (ages 15-44) to social norms and self-efficacy of females are found to be particularly important to steer dietary shifts. In the climate change debate, it has been scientifically acknowledged that people's beliefs and actions are formed by the values of their peer group, not by scientific facts[34, 35, 36]. Combined with our findings, this phenomenon emphasizes the importance and relevance of group dynamics instead of individual actions. Moreover, recent research suggests that collective-efficacy, which is the belief that one's group is capable of achieving change and which is not included in our model, may be a more important predictor of pro-environmental actions[37, 38]. This implies that system dynamics modeling, which addresses group dynamics by representing population heterogeneity with a compartmental approach, is highly suitable and can be very useful to investigate societal dynamics of lifestyle change.

The finding on the importance of social norms highlights the strong effect of feedbacks. Social norms create a reinforcing feedback loop that accelerates the adoption of low-carbon lifestyles as the *social transmission* loop in Figure 1 shows. Therefore, taking a feedback perspective in modelling societal dynamics is of utmost importance and this perspective can be facilitated by system dynamics which is a fundamentally feedback-oriented approach.

The scope of the model presented in this paper is limited to income, social norms, climate and health risk perception, as well as other psychological factors such as self-efficacy and response efficacy as the drivers of diet change behavior. Demographic heterogeneity is taken into account in terms of gender, age, and education level. However, there are several other factors and different dimensions of heterogeneity. For instance, social and cultural values transmitted by social interactions[21] affects public risk perception. Furthermore, cultural values and traditions strongly affect eating habits, especially lowering meat consumption[39, 40]. System dynamics modelling is an inherently interdisciplinary approach that allows representing such "soft" factors related to values and norms, in addition to easily measurable variables. Therefore, it can be useful in capturing social and cultural dimension of lifestyle change.

The modelling framework described in this paper integrates prominent theories from psychology on pro-environmental behavior and from management science on innovation diffusion. It also exemplifies how demographic heterogeneity can be addressed to model lifestyle changes. Therefore, the model is generalizable and transferrable to other lifestyle change domains such as mobility and residential energy consumption. Considering the growing call in the research community to explicitly include human behavior in integrated assessment models[41, 42, 43], this study presents an example in the nutrition domain that can easily be adopted for different lifestyle change domains and that can be connected with integrated assessment models.

Appendix I: Diet change model[4]

Psychological framework for diet change

The diet shifts extension to the FeliX Model was based on two complementary theories of psychology (Fig. 1): The Theory of Planned Behavior (TPB)[19] and the Protection Motivation Theory (PMT)[20, 44]. Both theories were used extensively to explain how people cope with personal threats[24], in particular healthy eating behaviors[45, 46] and environmental actions to deal with climate change[9, 47, 48, 49, 50]. The TPB and PMT are similar since they are both based on individual factors, yet they differ, especially since PMT has a specific risk focus[48]. We considered these two theories complementary in this study since they capture different dimensions of diet change behavior at the individual and social level.

The TPB distinguishes between behavioral intention and actual behavior. This distinction is important in the pro-environmental behavior context, since intentions often do not yield the desired impact on environmental factors such as energy use and carbon footprint[51, 52]. Behavioral intentions are formed by perceived behavioral control, or self-efficacy, which refers to the difficulty of performing a behavior as perceived by the individual; subjective norms, which refers to individuals' perception of how widely the behavior is accepted or followed in society; and attitude towards the behavior, which refers to whether the suggested behavior is evaluated positively or not.

According to the PMT, actions are determined by people's threat appraisal and coping appraisal. Threat appraisal is an individual assessment of the probability and severity of a threat, whereas coping appraisal refers to the extent to which an individual can and is willing to cope with the threat. Therefore, the coping appraisal is driven by self-efficacy, response efficacy, i.e. the belief whether the action will make an impact or not, and response cost, which is the cost of action in terms of time, finances, effort, etc.

Several empirical studies support the frameworks of the TPB and PMT for environmental actions and for diet change. For instance, people's eating behavior is heavily influenced by social norms, while information about the eating behaviors of similar others or desired groups has the most powerful influence[53]. In-group norms and goals determine the environmental appraisals and actions of individuals in this group[54]. Regarding threat appraisal, the perceived threat of climate events, either to self or others such as impoverished nations, is significant enough to alter the meat consumption of individuals[55]. Self-efficacy and response efficacy are even more significant to influence meat consumption behavior, while response cost has no substantial effect[55]. Environmental self-identity is a key indicator of meat consumption, although the most important factor is income for other environmental impacts such as energy

[4] From Eker et al. (2019)

use or carbon footprint[51]. Supporting the threat appraisal effect, citizens with more experience of disasters have a greater willingness to pay for climate change mitigation[56].

Demographic factors also play an important role in diet change. Moser and Kleinhückelkotten [51] found that gender is the most influential factor on meat consumption, as women have a stronger environmental self-identity and consume significantly less meat than men. Alló and Loureiro [56] state that women are more egalitarian than men, and hence more willing to adopt climate change mitigation actions. Therefore, we aggregated such gender differences in intrinsic, identity-driven motivation in the self-efficacy multiplier in the model, which represents an individual's belief that she can easily take action. Age is an important factor that affects the social transmission mechanism. As younger people are more susceptible to peer influence[57,58], the effect of norms on their behavior is higher than the effect on older people.

Model specification

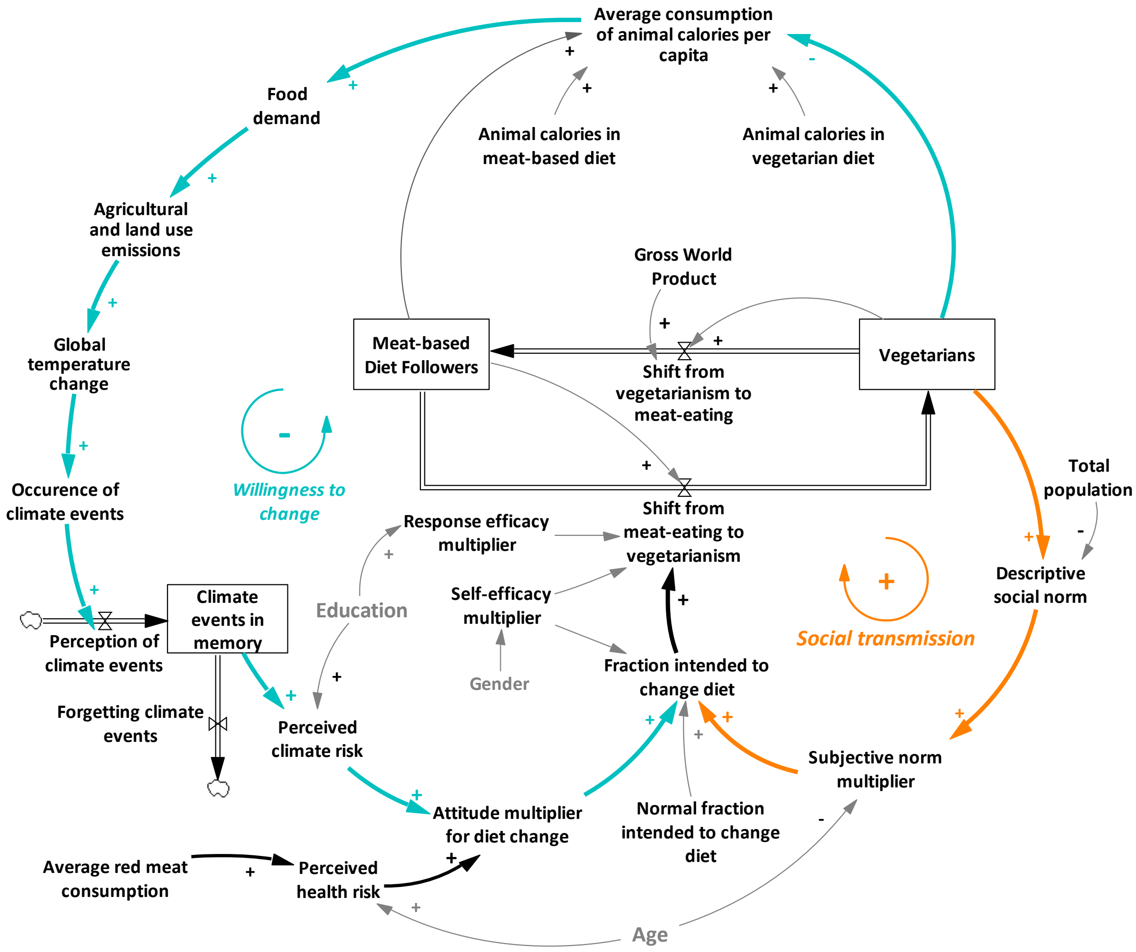


Figure A. 1: Stock-flow diagram of the dietary change model

The psychological framework was adjusted to a population-level mechanism with a public segmentation and innovation diffusion approach[26, 27,59]. The two main population segments are *Meat-based Diet Followers*, in other words, those who are potential adopters of a vegetarian diet, and *Vegetarians*. Figure A.1 visualizes the model structure with these two population segments, the flows between them, and the drivers of these flows. These two population segments are formulated as stock variables accumulating over time. The rate of *Shift from vegetarianism to meat-eating*, i.e. the flow from vegetarians to meat-eaters is a fraction of the *Vegetarians*, where this fraction is dependent on the Gross World Product (GWP) per capita. This mechanism represents the global increase in meat consumption, especially in developing countries, as the income level rises. The function $f_{income,meat}$ is calibrated according to the historical relation between GWP and meat consumption.

$$Shift\ from\ vegetarianism\ to\ meat\ eating = Vegetarians * f_{income,meat}\left(GWP\ per\ Capita\right) \quad (1)$$

The shift from meat-eating to a vegetarian diet (Equation 2) represents ‘behavior’ and depends on the intention as well as response efficacy and self-efficacy (Equation 3). While response efficacy and self-efficacy are assumed to be exogenous, response cost is excluded from the model due to its negligible role in diet change[55]. The behavioral intention, namely *Fraction intended to change diet*, is formulated as the multiplication of two factors that represent the attitude and subjective norms (Equation 4). The multiplicative formulation represents the amplifying effect of social norms, and the limited scale of attitude-dependent diet change without a high social norm effect. The *Subjective norm multiplier* is formulated as a logistic function of the *Descriptive social norm (*x_{norm}*)*, which is the fraction of *Vegetarians* in the total population. This logistic function (Equation 5) captures the phenomenon that the impact of norms on individuals is relatively low when the ratio of vegetarians in the total population is low, yet it increases rapidly in response to an increasing ratio of vegetarians and then stabilizes even though the vegetarian ratio is very high. L, k, and x0 represent the maximum value, steepness and inflection point of this logistic curve, respectively. Different parameterizations of this function form (Figure A.2) represent the age effect on the adoption of social norms.

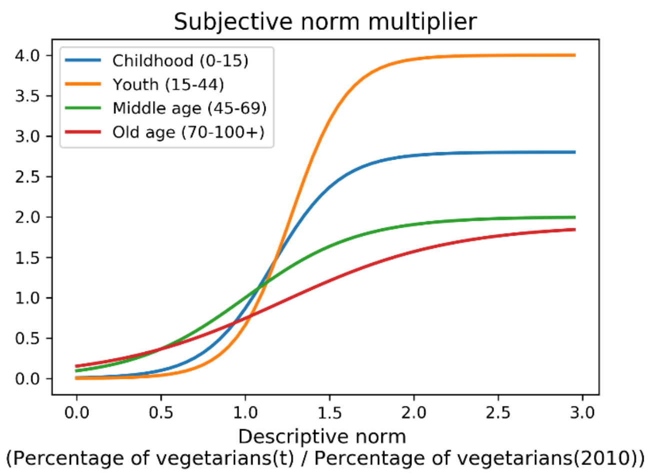


Figure A. 2: Subjective norm multiplier as a function of the descriptive norm (ratio of the percentage of vegetarians to its 2010 value). Age differences are taken into account with the assumption that young people are more responsive to social norms compared to children and older people

The *Attitude multiplier for diet change* is the average of climate and health risk multipliers (Equation 6). Each of these risk-induced attitude multipliers are also formulated as a logistic function. The *Climate risk multiplier* is a function of the number of climate events in public memory, with the assumption that a low number of climate events in the memory do not lead to a high pro-vegetarianism attitude, yet this attitude increases rapidly as the number of such events increases. This function form between risk and attitude is shown to create the highest sensitivity in global temperature change in the context of emission behavior[9]; hence it was chosen in this study. Equation 7 denotes the formulation of the climate risk multiplier with the parameters L, k and x0, which represent the maximum value, steepness and inflection point of the curve respectively. The variable input of this function, $x_{climate}$, is the ratio of *climate events in memory* to its value in 2010 (Equation 8). This normalization with respect to the 2010 values is to have a common reference point for the calibration of social norm, climate risk, and health risk effects on diet shift.

$$\textit{Shift from meat eating to vegetarianism} = \textit{Meat based diet followers} * \textit{Shift fraction of meat eaters} \tag{2}$$

$$\begin{aligned}\textit{Shift fraction of meat eaters} = \textit{Fraction intended to change diet} * \\ \textit{Self efficacy multiplier} * \\ \textit{Response efficacy multiplier}\end{aligned} \tag{3}$$

$$\begin{aligned}\textit{Fraction intended to change diet} = \textit{Normal fraction intended to change diet} * \\ \textit{Subjective norm multiplier} * \\ \textit{Attitude multiplier for diet change}\end{aligned} \tag{4}$$

$$\textit{Subjective norm multiplier} = \frac{L_{norm}}{1 + e^{-k_{norm} * (x_{norm}(t) - x0_{norm})}} \tag{5}$$

$$\textit{Attitude multiplier for diet change} = \left(\textit{Climate risk multiplier} + \textit{Health risk multiplier}\right)/2 \tag{6}$$

$$\textit{Climate risk multiplier}\left(t\right) = \frac{L_{climate}}{1 + e^{-k_{climate} * \left(x_{climate}(t) - x0_{climate}\right)}} \tag{7}$$

$$x_{climate}\left(t\right) = \frac{\textit{Climate events in memory}\left(t\right)}{\textit{Climate events in memory}\left(2010\right)} \tag{8}$$

Similarly, the *Health risk multiplier* is a logistic function of perceived health risk (Equation 9). Risk perception that triggers healthy eating behavior is most related to the objective health parameters individuals experience[60], such as blood sugar- and cholesterol levels. At the population level, the annual number of deaths attributed to red meat consumption is considered a proxy for perceived health risk (Equation 10). Moreover, death rates related to red meat also trigger a more widespread communication, reinforcing its role as a proxy for the perceived health risk. In the model, the number of deaths attributed to high red meat consumption was formulated endogenously as a function of the cumulative red meat consumption of the meat-based diet followers, not the entire population. The choice to consider cumulative red meat consumption instead of annual consumption was to include the effects of long-term consumption. This function was calibrated in a linear form for the age cohorts between 25 and 44, and in a logistic form for the other cohorts, following the data patterns in the period 1990-2017 reported by the Global Burden of Disease Study[61].

$$\textit{Health risk multiplier}\left(t\right) = \frac{L_{health}}{1 + e^{-k_{health} * \left(x_{health}(t) - x0_{health}\right)}} \tag{9}$$

$$x_{health}\left(t\right) = \frac{\textit{Deaths related to red meat}\left(t\right)}{\textit{Deaths related to red meat}\left(2010\right)} \tag{10}$$

Further explanation of model specification can be found in Supplementary Methods of Eker et a. (2019), which particularly explain

- how demographic heterogeneity is included in the model,
- compositions of different diet types and how the global food demand is calculated based on them,
- how extreme climate events and the public memory of them is modelled.

Parameterization and validation

This model of diet shift mechanisms heavily depends on the global number of vegetarians and meat-based diet followers, as well as on socio-psychological parameters that cannot be quantified straightforwardly. However, data availability about the global vegetarian population or similar demographic factors is considerably limited. The literature, if available, provides quantitative measures on an ordinal scale for the socio-psychological parameters, yet they do not precisely correspond to the model definitions. For instance, the relative contribution of self-efficacy, response-efficacy, and risk perception to diet change behavior can be inferred[46, 60]. However, for the social norm, climate risk, and health risk multipliers, only the function forms[9] and the difference between age and education groups could be qualitatively estimated.

Therefore, we quantified the model in three complementary ways: (i) Initialization based on the estimate that there were approximately 1.5 billion (21.5%) vegetarians in the world in 2010[62]; (ii) calibration of behavioral parameters according to the historical consumption of various food categories, and according to a reference simulation with an increasing vegetarian population due to increasing awareness in the western world, and (iii) empirical studies that indicate the relative values of the psychological parameters (e.g., the self-efficacy of women and men). In other words, we found the parameter values that minimize the difference between the historical data and model values of food consumption in step (ii). In step (iii), we checked if the relative calibrated values coincide with the qualitative information in the literature and re-iterated the calibration if not.

The parameter values obtained from the calibration procedure, however, are still highly uncertain, because they are calibrated according to variables that they are not directly linked to, and because multiple sets of parameter combinations could match the historical data. This is the reason for following an uncertainty-focused approach in this study rather than providing best-estimate projections, for using the model to explore various assumptions and for identifying the most influential of these uncertain parameters.

The approaches to and perspectives on validation differ across different modelling fields[63]. In this study, we used a combination of validation approaches from management science[64], and employed a historical data comparison for the food and land use sector, as well as expert reviews about psychological mechanisms. In particular, we compared the model output to historical data on *Agricultural Land, Forest Land* and *Food Supply*, which are directly affected by the food demand induced by diet shifts. We also cross-validate the model with the output of an established land use model, the Global Biosphere Management Model (GLOBIOM)[65].

Appendix II: The reference values of the model inputs and their uncertainty ranges used in sensitivity simulations

Uncertainties	Description	Reference	Min	Max
Response efficacy multiplier[noEd]	The parameter that represents the effect of response efficacy as a relative/fractional multiplier on the diet shift. It is dependent on the education level, therefore specified for the four education segments of the population.	0.8	0.4	1.2
Response efficacy multiplier[primary]		0.9	0.45	1.35
Response efficacy multiplier[secondary]		1	0.5	1.5
Response efficacy multiplier[tertiary]		1.2	0.6	1.8
Self efficacy multiplier[male]	The parameter that represents the effect of self efficacy as a relative multiplier on the diet shift. It is dependent on gender, i.e. higher for females, hence specified for the two demographic groups.	0.8	0.4	1.2
Self efficacy multiplier[female]		1.2	0.6	1.8
L risk attitude	The parameters that define the function between the perceived proportional climate risk (x) and attitude towards diet change (Supplementary Figure 3). The function formulation is $\frac{L}{1+e^{-k(x-x_0)}}$.	2	1	3
k risk attitude		3	1.5	4.5
x0 risk attitude		1	0.5	1.5
L social norm["10-14"]	The parameters that define the function between the percentage of vegetarians with respect to its 2010 value (x) and the social norm multiplier (Supplementary Figure 2). The function formulation is $\frac{L}{1+e^{-k(x-x_0)}}$. The influence of social norms depends on age, therefore this function is defined for 4 age groups, being childhood, youth, middle age and old age. The population cohort “10-14” is for the childhood group, “20-24” is for the youth, “45-49” is for middle age, and “80-84” is for the old age.	2.8	1.4	4.2
k social norm["10-14"]		5	2.5	7.5
x0 social norm["10-14"]		1.16	0.58	1.74
L social norm["20-24"]		4	2	6
k social norm["20-24"]		6	3	9
x0 social norm["20-24"]		1.27	0.635	1.905
L social norm["45-49"]		2	1	3
k social norm["45-49"]		2	1	3
x0 social norm["45-49"]		1	0.5	1.5
L social norm["80-84"]		1.9	0.95	2.85
k social norm["80-84"]		1	0.5	1.5
x0 social norm["80-84"]		1.22	0.61	1.83
Normal fraction intended to change diet	A reference value for the fraction of meat-based diet followers who intend to change their diet.	0.003	0.0015	0.0045
Time to forget climate events	The average duration (years) climate events remain in the public memory.	2	1	3
Climate Risk Perception Delay[noEd]	The average number of years it takes to perceive the observed climate events as future risks. This perception depends on the education level.	10	5	15
Climate Risk Perception Delay[primary]		8	4	12
Climate Risk Perception Delay[secondary]		5	2.5	7.5
Climate Risk Perception Delay[tertiary]		3	1.5	4.5
L health risk attitude["25-29"]	The parameters that define the function between the health risk with respect to its 2010 value (x) and the health risk multiplier (Supplementary Figure 4). The function formulation is $\frac{L}{1+e^{-k(x-x_0)}}$. Health risk is a factor only for the ages above 25. The	5	2.5	7.5
L health risk attitude["45-49"]		4	2	6
L health risk attitude["80-84"]		2.5	1.25	3.75
k health risk attitude["25-29"]		6	3	9
k health risk attitude["45-49"]		3.5	1.75	5.25

k health risk attitude["80-84"]	population cohort "25-29" is for the youth (25-44), "45-49" is for middle age (45-69), and "80-84" is for the old age (70-100+).	2	1	3
x0 health risk attitude["25-29"]		1	0.5	1.5
x0 health risk attitude["45-49"]		1.5	0.75	2.25
x0 health risk attitude["80-84"]		1	0.5	1.5

References

1. Grubler A, Wilson C, Bento N, Boza-Kiss B, Krey V, McCollum DL, *et al.* A low energy demand scenario for meeting the 1.5 °C target and sustainable development goals without negative emission technologies. *Nature Energy* 2018, **3**(6)**:** 515-527.
2. Stehfest E, Bouwman L, Van Vuuren DP, Den Elzen MG, Eickhout B, Kabat P. Climate benefits of changing diet. *Climatic change* 2009, **95**(1-2)**:** 83-102.
3. Tilman D, Clark M. Global diets link environmental sustainability and human health. *Nature* 2014, **515**(7528)**:** 518.
4. Springmann M, Clark M, Mason-D'Croz D, Wiebe K, Bodirsky BL, Lassaletta L, *et al.* Options for keeping the food system within environmental limits. *Nature* 2018, **562**(7728)**:** 519-525.
5. IPCC. Special Report on Global Warming of 1.5 °C: Intergovernmental Panel on Climate Change; 2018.
6. IPCC. Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse gas fluxes in Terrestrial Ecosystems: Intergovernmental Panel on Climate Change; 2019.
7. Obersteiner M, Walsh B, Frank S, Havlík P, Cantele M, Liu J, *et al.* Assessing the land resource–food price nexus of the Sustainable Development Goals. *Science Advances* 2016, **2**(9).
8. FAO. Food Balance Sheets. Food and Agriculture Organization of the United Nations; 2018.
9. Beckage B, Gross LJ, Lacasse K, Carr E, Metcalf SS, Winter JM, *et al.* Linking models of human behaviour and climate alters projected climate change. *Nature Climate Change* 2018**:** 1.
10. Eker S, Reese G, Obersteiner M. Modelling the drivers of a widespread shift to sustainable diets. *Nature Sustainability* 2019, **2:** 725-735.
11. Smith P, Bustamante M, Ahammad H, Clark H, Dong H, Elsiddig EA, *et al.* Agriculture, forestry and other land use (AFOLU). *Climate change 2014: mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, 2014.
12. Foley JA, Ramankutty N, Brauman KA, Cassidy ES, Gerber JS, Johnston M, *et al.* Solutions for a cultivated planet. *Nature* 2011, **478**(7369)**:** 337-342.
13. Steffen W, Richardson K, Rockström J, Cornell SE, Fetzer I, Bennett EM, *et al.* Planetary boundaries: Guiding human development on a changing planet. *Science* 2015, **347**(6223)**:** 1259855.
14. Willett W, Rockström J, Loken B, Springmann M, Lang T, Vermeulen S, *et al.* Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems; 2019. Report No.: 0140-6736.

15. Godfray HCJ, Aveyard P, Garnett T, Hall JW, Key TJ, Lorimer J*, et al.* Meat consumption, health, and the environment. *Science* 2018, **361**(6399)**:** eaam5324.
16. Rydzak F, Obersteiner M, Kraxner F, Fritz S, McCallum I. FeliX3 – Impact Assessment Model: Systemic view across Societal Benefit Areas beyond Global Earth Observation. Laxenburg: International Institute for Applied Systems Analysis (IIASA); 2013.
17. Walsh BJ, Rydzak F, Palazzo A, Kraxner F, Herrero M, Schenk PM*, et al.* New feed sources key to ambitious climate targets. *Carbon balance and management* 2015, **10**(1)**:** 26.
18. Walsh B, Ciais P, Janssens IA, Peñuelas J, Riahi K, Rydzak F*, et al.* Pathways for balancing CO2 emissions and sinks. *Nature Communications* 2017, **8:** 14856.
19. Ajzen I. The theory of planned behavior. *Organizational Behavior and Human Decision Processes* 1991, **50**(2)**:** 179-211.
20. Boer H, Seydel ER. Protection motivation theory. In: Conner M, Norman P (eds). *Predicting health behaviour: Research and practice with social cognition models*. Open University Press: Maidenhead, BRK, England, 1996.
21. Slovic P. Perception of risk. *Science* 1987, **236**(4799)**:** 280-285.
22. Fox N, Ward K. Health, ethics and environment: a qualitative study of vegetarian motivations. *Appetite* 2008, **50**(2-3)**:** 422-429.
23. Stehfest E. Food choices for health and planet. *Nature* 2014, **515:** 501.
24. Westhoek H, Lesschen JP, Rood T, Wagner S, De Marco A, Murphy-Bokern D*, et al.* Food choices, health and environment: Effects of cutting Europe's meat and dairy intake. *Global Environmental Change* 2014, **26:** 196-205.
25. Springmann M, Godfray HCJ, Rayner M, Scarborough P. Analysis and valuation of the health and climate change cobenefits of dietary change. *Proceedings of the National Academy of Sciences* 2016, **113**(15)**:** 4146-4151.
26. Rogers EM. *Diffusion of innovations*. Simon and Schuster, 2010.
27. Bass FM. A new product growth for model consumer durables. *Management science* 1969, **15**(5)**:** 215-227.
28. Vranken L, Avermaete T, Petalios D, Mathijs E. Curbing global meat consumption: Emerging evidence of a second nutrition transition. *Environmental Science & Policy* 2014, **39:** 95-106.
29. Saltelli A, Ratto M, Andres T, Campolongo F, Cariboni J, Gatelli D*, et al. Global sensitivity analysis: the primer*. John Wiley & Sons, 2008.
30. Saltelli A, Annoni P, Azzini I, Campolongo F, Ratto M, Tarantola S. Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. *Computer Physics Communications* 2010, **181**(2)**:** 259-270.
31. Sobol IM. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and computers in simulation* 2001, **55**(1-3)**:** 271-280.
32. Herman J, Usher W. SALib: an open-source Python library for sensitivity analysis. *The Journal of Open Source Software* 2017, **2**(9).
33. Saltelli A. Making best use of model evaluations to compute sensitivity indices. *Computer physics communications* 2002, **145**(2)**:** 280-297.
34. Hayhoe K. When facts are not enough. *Science* 2018, **360**(6392)**:** 943-943.
35. Kahan D. Fixing the communications failure. *Nature* 2010, **463**(7279)**:** 296.

36. Kahan DM, Peters E, Wittlin M, Slovic P, Ouellette LL, Braman D, *et al.* The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nature climate change* 2012, **2**(10)**:** 732.
37. Reese G, Junge E. Keep on rockin'in a (plastic-) free world: Collective efficacy and pro-environmental intentions as a function of task difficulty. *Sustainability* 2017, **9**(2)**:** 200.
38. Jugert P, Greenaway KH, Barth M, Büchner R, Eisentraut S, Fritsche I. Collective efficacy increases pro-environmental intentions through increasing self-efficacy. *Journal of Environmental Psychology* 2016, **48:** 12-23.
39. Macdiarmid JI, Douglas F, Campbell J. Eating like there's no tomorrow: Public awareness of the environmental impact of food and reluctance to eat less meat as part of a sustainable diet. *Appetite* 2016, **96:** 487-493.
40. Pohjolainen P, Vinnari M, Jokinen P. Consumers' perceived barriers to following a plant-based diet. *British Food Journal* 2015, **117**(3)**:** 1150-1167.
41. Steg L. Limiting climate change requires research on climate action. *Nature Climate Change* 2018, **8**(9)**:** 759-761.
42. McCollum DL, Wilson C, Pettifor H, Ramea K, Krey V, Riahi K, *et al.* Improving the behavioral realism of global integrated assessment models: An application to consumers' vehicle choices. *Transportation Research Part D: Transport and Environment* 2017, **55:** 322-342.
43. Pettifor H, Wilson C, McCollum D, Edelenbosch OY. Modelling social influence and cultural variation in global low-carbon vehicle transitions. *Global Environmental Change* 2017, **47:** 76-87.
44. Rogers RW. A protection motivation theory of fear appeals and attitude change1. *The journal of psychology* 1975, **91**(1)**:** 93-114.
45. Povey R, Conner M, Sparks P, James R, Shepherd R. The theory of planned behaviour and healthy eating: Examining additive and moderating effects of social influence variables. *Psychology & Health* 2000, **14**(6)**:** 991-1006.
46. de Ridder D, Kroese F, Evers C, Adriaanse M, Gillebaart M. Healthy diet: Health impact, prevalence, correlates, and interventions. *Psychology & health* 2017, **32**(8)**:** 907-941.
47. Tikir A, Lehmann B. Climate change, theory of planned behavior and values: a structural equation model with mediation analysis. *Climatic change* 2011, **104**(2)**:** 389-402.
48. Bockarjova M, Steg L. Can Protection Motivation Theory predict pro-environmental behavior? Explaining the adoption of electric vehicles in the Netherlands. *Global Environmental Change* 2014, **28:** 276-288.
49. Aerts JCJH, Botzen WJ, Clarke KC, Cutter SL, Hall JW, Merz B, *et al.* Integrating human behaviour dynamics into flood disaster risk assessment. *Nature Climate Change* 2018, **8**(3)**:** 193-199.
50. Renger D, Reese G. From equality-based respect to environmental activism: Antecedents and consequences of global identity. *Political Psychology* 2017, **38**(5)**:** 867-879.
51. Moser S, Kleinhückelkotten S. Good Intents, but Low Impacts: Diverging Importance of Motivational and Socioeconomic Determinants Explaining Pro-Environmental Behavior, Energy Use, and Carbon Footprint. *Environment and behavior* 2017**:** 0013916517710685.

52. Bamberg S, Möser G. Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. *Journal of environmental psychology* 2007, **27**(1)**:** 14-25.
53. Robinson E, Thomas J, Aveyard P, Higgs S. What everyone else is eating: a systematic review and meta-analysis of the effect of informational eating norms on eating behavior. *Journal of the Academy of Nutrition and Dietetics* 2014, **114**(3)**:** 414-429.
54. Fritsche I, Barth M, Jugert P, Masson T, Reese G. A Social Identity Model of Pro-Environmental Action (SIMPEA). *Psychological Review* 2018, **125:** 245-269.
55. Hunter E, Röös E. Fear of climate change consequences and predictors of intentions to alter meat consumption. *Food Policy* 2016, **62:** 151-160.
56. Alló M, Loureiro ML. The role of social norms on preferences towards climate change policies: A meta-analysis. *Energy Policy* 2014, **73:** 563-574.
57. Steinberg L, Monahan KC. Age Differences in Resistance to Peer Influence. *Developmental psychology* 2007, **43**(6)**:** 1531-1543.
58. Knoll LJ, Leung JT, Foulkes L, Blakemore S-J. Age-related differences in social influence on risk perception depend on the direction of influence. *Journal of Adolescence* 2017, **60:** 53-63.
59. Sterman JD. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin/McGraw-Hill: Boston, 2000.
60. Renner B, Schwarzer R. The motivation to eat a healthy diet: How intenders and nonintenders differ in terms of risk perception, outcome expectancies, self-efficacy, and nutrition behavior. *Polish Psychological Bulletin* 2005, **36**(1)**:** 7-15.
61. GHDx. Global Burden of Disease Study 2017. Seattle, USA: University of Washington; 2019.
62. Leahy E, Lyons S, Tol RS. An estimate of the number of vegetarians in the world: ESRI working paper; 2010.
63. Eker S, Rovenskaya E, Obersteiner M, Langan S. Practice and perspectives in the validation of resource management models. *Nature Communications* 2018, **9**(1)**:** 5359.
64. Barlas Y. Formal Aspects of Model Validity and Validation in System Dynamics. *System Dynamics Review* 1996, **12**(3)**:** 183-210.
65. Valin H, Havlík P, Forsell N, Frank S, Mosnier A, Peters D, *et al*. Description of the GLOBIOM (IIASA) model and comparison with the MIRAGE-BioF (IFPRI) model. *Crops* 2013, **8:** 3.1.