Global land use and the future of sustainable consumption: projections of a coupled social-land use model

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Throughout history, agricultural land use activities have shaped the environment and its inhabitants. Humans have sought to maintain their well-being for centuries by finding revolutionary ways to produce and gather food. But challenges that are new to us–both in nature and intensity–face the human race and its planet as we move further into the 21^{st} century. Global food demand is currently at its peak and is projected to grow in the near future due to growing global population and global affluence. Subsequently, pressure on the agricultural system is expected to increase to meet the elevated demand. Agricultural expansion, a possible pathway for meeting increasing demand, has been shown to bring with it severe impacts on climate, environment and ecosystems. While several land use mitigation strategies have been thoroughly explored in the literature, they have mostly been centered around policy regarding land use management and investment in agricultural technology. In most of the models, future dietary patterns of populations are assumed to behave independently from land use change. The immense potential of sustainable consumption in land use mitigation, stimulated by desires to avoid agricultural expansion into sensitive ecosystems, has only been explored through scenario constructions. Little effort has been spent on understanding how sustainable consumption might begin evolving in a population as a behaviour in response to land use dynamics. This thesis introduces a minimal mathematical model based on evolutionary game theory that couples human behavioural dynamics with land-use system dynamics. This coupled human-environment model helps in gaining a better understanding of the evolution of sustainable diets within populations while making global land use projections till 2100 under multiple future socio-economic scenarios. Results in this thesis highlight the direct impact of social processes on global agricultural land use and underline the barriers and drivers of human consumption behaviour. The model framework lays the foundation for further developments in complex coupled human-land system models that focus on gaining deeper insights into system dynamics and possible future outcomes of interventions.

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Dedication

To friends and family,

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Chapter 1

Introduction

1.1 Global agricultural land use and its history

Global agricultural land is broadly defined as the land that is used for generating the food demand of the world population. It includes land that is used as cropland and also land that is used for livestock rearing (pastureland and land for feed generation). According to the 2018 global land use data from the United Nations Food and Agriculture Organization dataset UN FAOSTAT [33], 27 % of the total available land surface on Earth is used for livestock rearing and 7% of it is used for the purpose of cropland.

Agricultural land currently occupies the largest share in global land distribution. Land used to generate our current food demand (34 % of land surface on Earth) is more than land used for any other purpose - anthropogenic or non-anthropogenic (including barren land which constitutes 19 % of total available land surface). Forests, glaciers, shrub, freshwater and urban area respectively cover 26%, 10%, 8%, 1% and 1% of available land surface on Earth.

Since the Industrial Revolution in 1800, amount of land required for generating the global food demand has grown 385 % from 1.12 billion hectares to 4.86 billion hectares. Between 1961 and 2013, global agricultural land expanded from 4.45 billion hectares to 4.88 billion hectares (a 7 % increase). Cropland grew from 1.38 to 1.57 billion hectares while pasture land grew from 3.07 to 3.33 billion hectares [33]. To put these numbers into perspective, mainland China is approximately a billion hectares in its geographical coverage (0.96 billion hectares) and Africa, is very close to 3 billion hectares.

The area values cited here also account for land that generates the food that ends up being wasted by humankind. In a special report [29], the FAO cites that in 2007, approximately 1.3 billion hectares of global agricultural land was spent to generate wasted food while 3.5 billion hectares was spent to generate the food that was actually consumed.

1.2 Perils of agricultural expansion and agricultural intensification

Agricultural land use brings with it severe impacts on the environment, climate and the ecosystem. The process of increasing agricultural area is called agricultural expansion while the process of increasing agricultural productivity of a given area of land is termed as agricultural intensification. Both of these processes, aimed at achieving higher food production, come with a cost to the environment.

Currently, land use contributes to 30% of anthropogenic Green House Gas (GHG) emissions. Emissions from land use can be categorized into two broad sectors - i) emissions due to change in forest cover (triggered by agricultural expansion) and ii) emissions due to agricultural practices (triggered by agricultural intensification). In the 1990s, the larger portion of the emissions was contributed by deforestation. However, in 2010, agriculture became the larger component while contributing to 11.2% of total GHG emissions [99]. Its yearly emission of methane and nitrous oxide contributes to 15% of anthropogenic emissions. Agriculture is also the largest contributor to global reactive Nitrogen (Nr) pollution which poses a variety of threats to the environment and the ecosystem [11, 96, 36, 103]. A significant portion of Nr losses incurred in the agricultural system, through waste, sewage and poor manure management, is responsible for the production of the ozone depleting agent N_2O. One of the primary sources of reactive nitrogen in agriculture is the excessive use of inorganic fertilizers. Free reactive nitrogen in combination with nutrient runoff from industry and agriculture causes eutrophication which results in damage of terrestrial and aquatic ecosystems [22, 89]. With no mitigation, Nr pollution from agriculture in 2050 is expected to rise to 102-156% of the 2010 value – which is way above the critical environmental threshold [11]. The severe impact of agricultural expansion on biodiversity and wildlife habitat loss has been well documented in the Millennium Ecosystem Assessment of 2005 [5]. The largest emitting sector in agriculture is livestock rearing. Per year, the livestock industry emits 7.1 giga tonnes of CO_2 equivalent representing 14.5% of all anthropogenic emissions [38]. In livestock rearing, cattle rearing (for beef, milk, manure and draft power) contributes the most to emissions (65 % of total). With rising demands for animal food product, these emission numbers are expected to grow in the near future.

1.3 Drivers of Global Agricultural Land Use

Obviously, it is of great interest to predict the future status of global agricultural land use. In order to do that it is important to understand the various drivers of land-use. Complex yet identifiable drivers of global agricultural land use can be compartmentalized into two broad categories - (a) the demand side and (b) the supply side. An overview of them is provided in the following subsections:

1.3.1 The Demand Side: a brief history and possible futures

Understandably, global agricultural land use has a monotonically increasing relationship with global demand for food, provided other factors remain as they are. The global demand for food has shown an increasing trend historically. From 1961 to 2013, the UN FAOSTAT data shows that the global demand of food went up from 6.4 trillion kilocalories per day to 19.4 trillion kilocalories per day. There are two reasons for the tripling. Firstly, over this period, global population grew from 3 billion to 7.1 billion. Secondly, the average per capita consumption has grown from 1800 kcals per day to 2600 kcals per day over the same period (including per capita wastage). Simultaneous growth in global population and average per capita consumption has caused this increase in global food demand over the span of 53 years.

The future of the demand side depends on the future of population growth and the future of global consumption pattern. Although there exists many widely accepted projections for future global population [67, 49, 77, 26], projections for future consumption patterns are rare in the literature due to the complexity of the problem. Some recent efforts [12, 61, 105, 74, 1] have identified the major drivers in food consumption. In these studies, scenario wise predictions for dietary pattern are made till 2100. Models in these studies are reductive since they assume dietary patterns to be just non-linear functions of per capita income and time. Effect of behavioral choices are eliminated in them.

Between 1961 and 2013, our average per capita diet has increased simultaneously with the fraction of animal product in our diet [1]. In the span of these 53 years, weighted average of the fraction of animal product in our diet (weighted with respect to population of nations) has increased from 9 % to 15%. Figure 1.1 shows how diets and animal product portion of diets have evolved with years in countries. Both of these quantities are scattered

[1]The Food Balance Sheet categorizes food into 21 categories out of which I classify 7 to be animal products. These are Bovine Meat, Mutton and Goat Meat, Pig meat, Poultry Meat, Eggs, Butter/Ghee and Milk.

against the mean income of nations at respective years. Due to uneven distribution in the density of the data points in Figure 1.1, it could be hard to decipher the qualitative trend of the data. So, data in Figure 1.1 is recast in a log-log scale in Figure 1.2 for better clarity. From 1.2 it is possible to see that a correlation exists between per capita income and per capita consumption (in the logarithmic scales) at the national level.

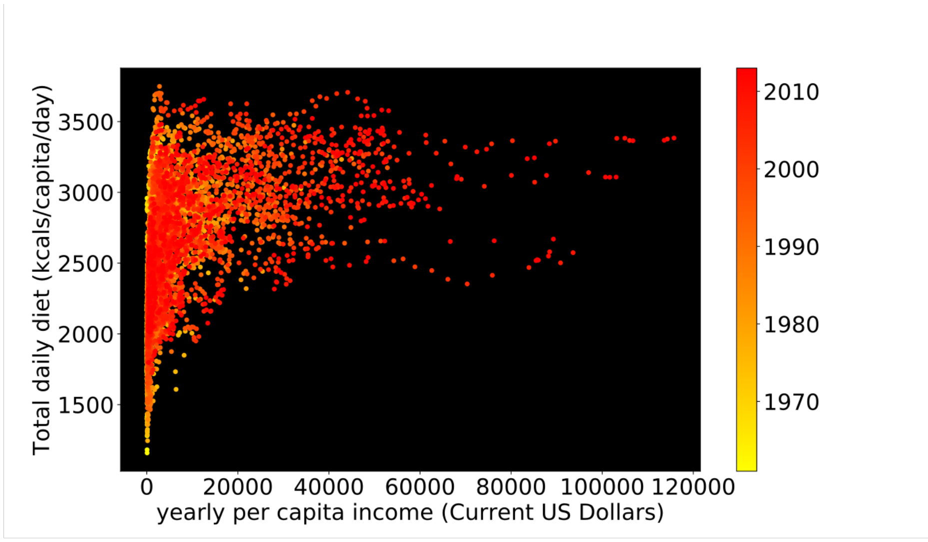
Although projections of demand are complicated, several global projections have been made by assuming scenarios of dietary patterns. For example, in some studies, storyline scenarios of reduced meat consumption and plant based diets are constructed to make projections for future values of demand [74, 12, 3, 102, 53]. These studies also project results for the status quo scenario and enhanced meat intake scenario. More or less, all of these projections converge towards the global average of 3000 kcals per capita per day in 2030 and 3100 kcals per capita per day in 2050. They project animal product consumption to reach a global average of 700 kcals per capita day in 2050 [12].

In the next subsection we will observe why the distribution of total diet over food groups matter in answering the bigger question of global land use.

1.3.2 The Supply Side: a brief history and possible futures

At a given location, under a fixed set of external conditions, the amount of land required to produce equal quantities of two different food items varies depending upon their biological properties and the properties of the soil. When I use the term 'quantity' of a food item , I either refer to its weight (tonnes) or its energy equivalent (kcals per tonne). The property of the land that determines its productivity of a food item, X, is called its yield of X. For example, in 2013, the average yield of cereals in India was calculated to be around 2.96 tonnes per hectare [32]. Calculating yield from data is a theoretically easy task for food items that undergo minimal processing between land and table (e.g items in groups of fruits, vegetables, grains [2]). Whereas, for items with a complicated supply chain (items in groups of meats, dairy), this is not so easy. In fact, yield of meats is technically defined in the literature as the conversion factor between carcass weight of an animal and quantity of meat produced from it. It is not a simple task to calculate the area of land required to produce one glass of milk since one has to account for pastureland and the land that generated the feed for the source animal over its lifetime. Although challenging, there has been significant progress in calculating this value from data. For example, the model in

[2] for the most part in this thesis, I define a diet to consist of seven food groups. These are fruits, vegetables, grains, meats, dairy, sugar and oils. I define them in a later section.



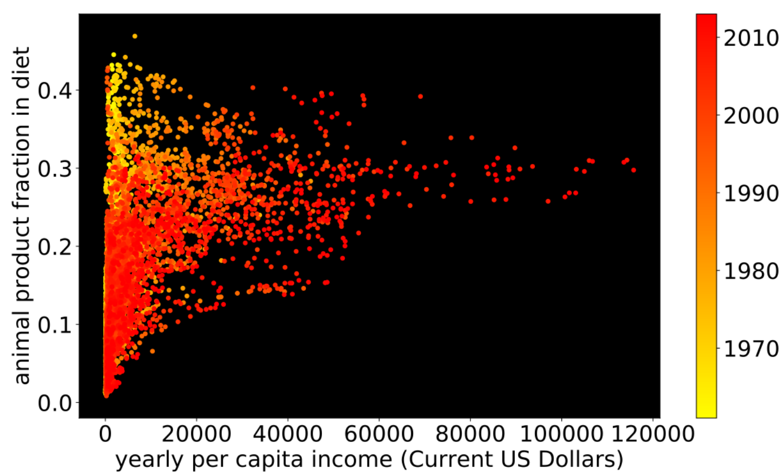


Figure 1.1: Average total daily diet and fraction of animal product in diets tend to increase with increase in mean income of countries. Data is reported by the UN FAOSTAT in the Food Balance Sheet dataset. Each dot in this figure represents a country in a particular year.

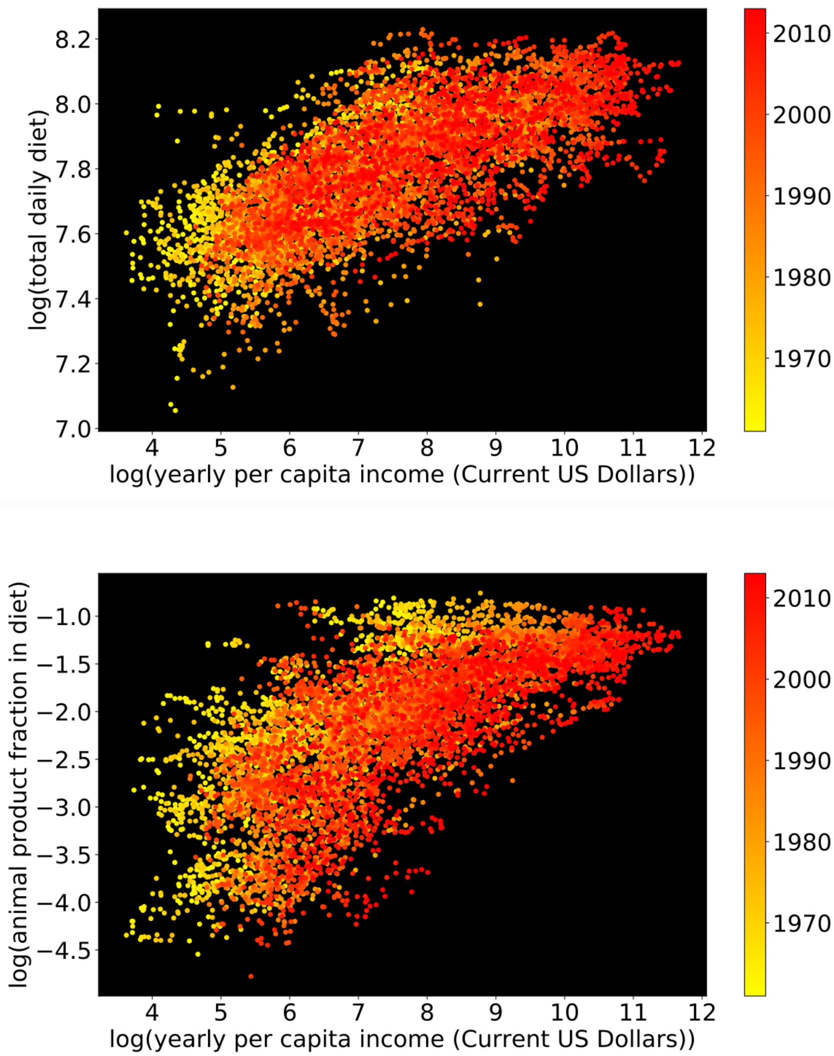


Figure 1.2: Plots in Figure 1.1 recast in log-log axis. Each dot in this figure represents a country in a particular year.

Rizvi et al. [78] can calculate the yearly yield of items in meats and dairy groups for a given country from the FAO datasets.

Calculations for yield become even more complicated when trade is factored in. 'Effective weighted yield' of an item X in a country i can be defined as the weighted average of yields of X in trading partners of i (including itself). The yields are weighted with the quantity of item that is imported from each source nation. Let y_i^X be the yield of X in i. If we assume that all of X in i comes from a set of sources S (that contains i), each j in S contributing q_j^X, then, the effective yield of X in i, $y_{eff,i}^X$, can be calculated using the following equation:

$$y_{eff,i}^X = \frac{\sum_{j \in S} q_j^X y_j^X}{\sum_{j \in S} q_j^x} \tag{1.1}$$

As calculated by the model in [78], effective yield of milk in Canada was approximately 32 tonnes per hectare in 2013. For USA, it was calculated to be 102 tonnes per hectare in the same year.

As yields of food items grow, land is spared for a fixed amount of food demand. Progress and distribution of agricultural technologies have historically shown to assist enhancement of yield values [98]. From 1961 to 2013, production gains achieved, globally, were primarily due to steady rate of growth of yields [15, 32]. In Figure 1.3, I show the time series of globally averaged effective yield for 20 items listed in the Food Balance Sheet. The items are grouped into eight categories such that all the items per category have similar yield values. Yields of almost all the items listed in the food balance sheet have gone up from their 1961 values. Bovine (cow) and Ovine meat (sheep and goat) have the lowest global effective yield. In 2013, global average of bovine meat yield was approximately 0.05 tonnes per hectare. To produce a kilogram of beef (approximately 2500 kcals) in 2013, one would have expected to require 0.02 hectares of land. Similarly, let's take the example of Potatoes that fall under the food balance sheet food item 'Starchy Roots'. Globally averaged effective yield of potatoes in 2013 was 13.13 tonnes per hectares. To produce a kilogram of potatoes (approximately 770 kcals) over 2013, one would have expected to require 7.6×10^{-4} hectares. Due, to a significant difference between the effective yield of edible items, dietary distribution across food groups play a major role in determining how much land is required to meet the global food demand. A more meat-centric diet would naturally require more area of land to generate than a comparatively greener substitute.

Recently, several studies from the literature of agricultural science have claimed that the future of agricultural intensification (the process of achieving higher productivity of land with years) is uncertain. For example, in rich nations, several major crops have been shown to reach their yield ceilings [31, 25, 18]. There have also been studies that suggest that deceleration in yield rates, globally, have been caused due to reduction in investment in agricultural research and lowering of food production prices. [69]. Furthermore, it is expected that land productivity will be negatively affected by climate change induced effects like increased peak temperatures, increased severity and frequency of droughts, floods and extreme weather events [58]. Several research papers have charted future pathways for global agricultural system such that projected demands of the future are met sustainably [98, 39]. In those papers, the authors conclude that agricultural development directed towards higher achievement in technology (raising the yield ceilings) and technological transfer (closing yield gaps between nations) can meet 2050 crop demands with least land clearing and GHG emissions.

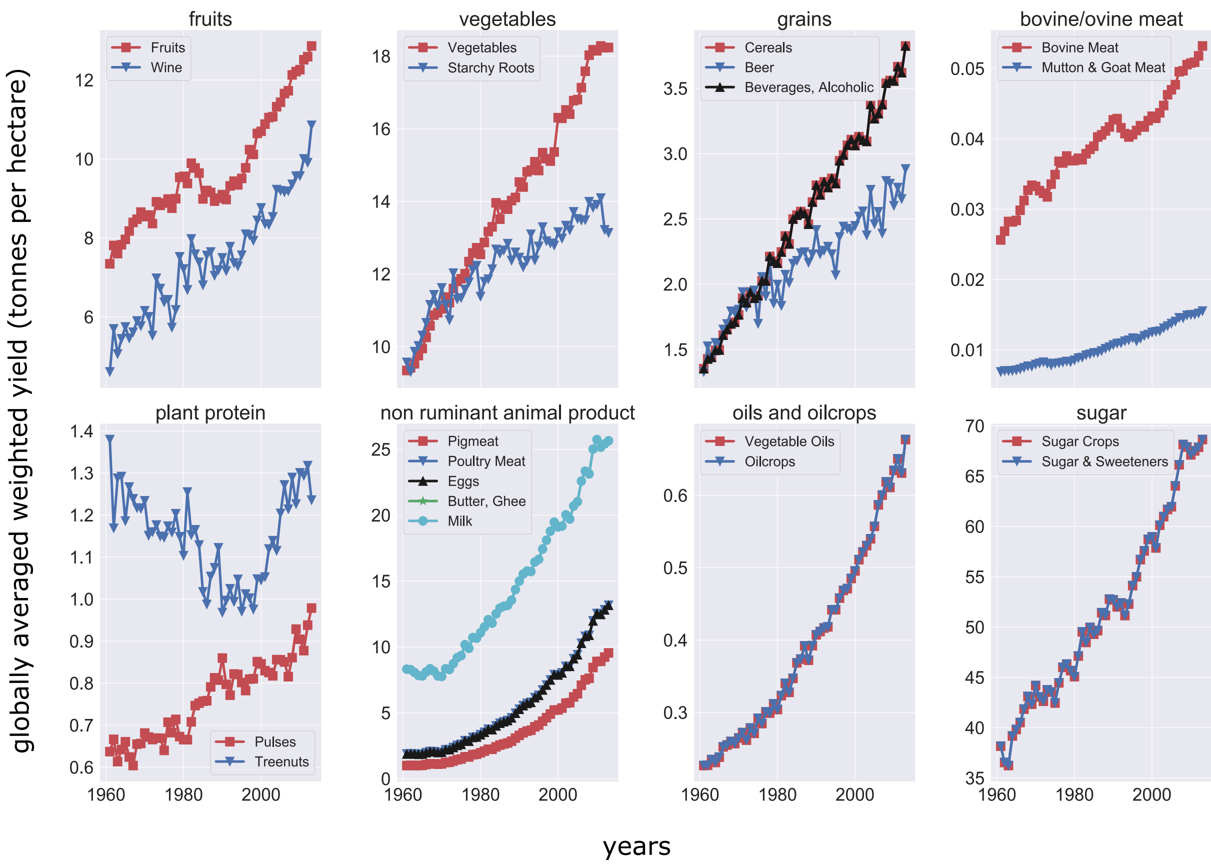


Figure 1.3: Globally averaged weighted yields of 20 food items listed in the food balance sheets of UN FAOSTAT dataset. Weighted yield values are calculated using the model described in Rizvi et al. [78]

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1.4 What is a dietary distribution?

One of the central relationships explored in this thesis is the one between dietary consumption and global land use. In the earlier sections a brief overview was provided on global land use and its drivers. In this section, I define the term dietary distribution. As mentioned earlier, I define a diet to consist of seven primary food groups. These are - fruits, vegetables, grains, meats (contains meats and pulses), dairy, sugar (also termed as discretional) and oils. This specific food group breakdown was borrowed from Rizvi et al. [78].

A dietary distribution is defined as a breakdown of the daily caloric intake into these seven groups. In the past, many units have been used while defining a diet. Some of the popular ones are 'cups'(1 cup = 16 US tablespoons), kilocalories, grams, ounce-equivalent and teaspoons. This thesis adheres to the kilocalorie standard while defining a diet. For example, USDA's 2010 dietary recommendation for the 2000 kcals/day limit was as follows:

- Fruit: 2 Cups
- Vegetables: 2.5 Cups
- Grains: 6 cups
- Whole-grain portion: 3 ounce equivalent
- Meat and Beans: 5.5 ounce-equivalent
- Milk: 3 cups
- Oils: 6 teaspoons
- Discretionary calorie allowance: 267 kilocalories

Recommended daily serving sizes can be converted to equivalent masses (and hence calories) using the FAO food balance sheet handbook [50]. The above recommended diet, when converted to kilocalories and separated into the pre-defined food groups, transforms to:

- Fruits: 186 kcals
- Vegetables: 87 kcals

Food Group name	Food Balance Sheet items under food groups
Fruits	Fruits - Excluding Wine, Wine
Vegetables	Vegetables, Starchy Roots
Grains	Cereals - Excluding Beer, Beer, Beverages, Alcoholic
Meats (and Pulses)	Pulses, Treenuts, Bovine Meat, Mutton & Goat Meat, Pig meat, Poultry Meat, Oil crops, Eggs
Dairy	Milk - Excluding Butter, Butter, Ghee
Oils	Vegetable Oils
Sugar	Sugar Crops, Sugar and Sweetners, Stimulants

Table 1.1: Table defining the food groups by aggregating food balance sheet items under them. The left hand column contains the food group name while the right hand column lists the food balance sheet items falling under the group name.

- Grains: 266 kcals
- Meats (and Pulses): 299 kcals
- Dairy: 727 kcals
- Oils: 239 kcals
- Sugar (discretionary): 267 kcals

On addition, the group calories in the above breakdown sum up to 2000 kcals. This confirms the correctness of the conversion as the initial recommendation was meant for the 2000 kcals/day level.

1.4.1 Country level data for average dietary distribution

The food balance sheet of the UN FAOSTAT [32] lists data for 21 food items that more or less cover the spectrum of human food intake. Items that do not require land to produce are discarded from the list (like fish meat and seafood). In Table 1.1 I aggregate these 21 items into their respective food groups.

For each of these 21 items, food supply data are provided for countries between the years 1961 and 2013. Food supply is a measure that evaluates the average per capita

	Food Supply, 2013 (kcals/capita/day)			
Food Group	USA	Canada	Brazil	India
Fruits	135	156	116	70
Vegetables	161	199	157	121
Grains	944	975	1064	1375
Meats (and Pulses)	617	639	708	215
Dairy	410	246	262	199
Oils	689	567	434	207
Sugar	621	451	440	237
Total	3577	3233	3181	2424

Table 1.2: Construction of average dietary distributions of USA, Canada, Brazil, India in 2013 using data from UN FAOSTAT food balance sheet [32].

calorie intake of a food item in a population. For example, food supply data for poultry meat consumption in Canada in 2013 was 145 kcals/capita/day. This means that, on average, in 2013, Canadians consumed 145 kcals of Poultry Meat per day. By using the extensive dataset provided by the UN FAOSTAT, country level data for average dietary distribution can be constructed by adding up food supply data for each item under a food group. An example is shown in Table 1.2. In Table 1.2, average dietary distributions for USA, Canada, Brazil and India are constructed and shown for the year 2013. From here on, I also refer to the average diet of a population as the demand of the population.

1.5 Is it possible to calculate land equivalent of a diet?

In this section I address the following question: "Is it possible to calculate how much land was required at a given year to generate the average diet of a population?" Although the answer to the above question is in the affirmative, there are nuances to be considered before introducing a method that performs this calculation.

Firstly, it is clear that demand (diet) to land conversion is not spatially independent because of spatial dependence of yield of food items. Due to difference in agricultural technologies and other equally important factors like soil quality and water availability, yield of food items vary largely across the globe (we have seen an example of this earlier). Spatial heterogeneity in effective yield of items is also caused due to the fact that international food trade is inherently heterogenous (all countries do not import same quantities from a fixed set of sources).

Secondly, all calculations for land are done on the yearly timescale. That is, the method I introduce, assumes that an entire population consumes an average diet for a year and then calculates the land equivalent of that consumption.

Thirdly, the model can only make calculations for years between 1961 and 2013 for countries that have been listed in the FAO food balance sheet. The model does not necessarily require one to input the actual average dietary distribution for a country to evaluate its land equivalent. For counter-factual analysis, one can also input a hypothetical diet for a country to evaluate its land equivalent at that year. For example, the model can calculate the amount of land that would have been spared if Americans consumed like Indians in the year 1972.

1.5.1 The Rizvi et al. [78] model: from diet to land

The original version of the model was built to study the global land use implication of the 2010 USDA dietary recommendation. With slight modification, the current form of the model, as presented here, allows land calculation for any dietary distribution in any country for any year between 1961 and 2013. This model can be found as a Python script in the following online repository: Saptarshi07/Dietary-Trends-Tools. The repository contains all demonstrations necessary to use the model.

Land calculation

I represent the Rizvi et al. model as a function, $R(.)$, that maps a diet $\mathbf{D}$, a country i, and a year t into a land use value. That is, if the population of i in year t consumed the average per capita diet $\mathbf{D}$, $R(\mathbf{D}, i, t)$ hectares of land would have been spent, globally, to generate the demand. For this function, t is an integer such that $1961 \leq t \leq 2013$. A diet is defined, mathematically, as a column vector of length 7. Numeric value of the vector components represent daily caloric intake in the food groups of fruits, vegetables, grains, meats, dairy, oils and sugar. For every item in the food balance sheet (that is assigned a parent food group), data for food supply quantity (in kilograms per capita per day) and food supply (kcals per capita per day) is provided simultaneously for a country at a year. This helps in evaluating the energy to mass conversion factor for a food item j in a country i at a year t. Let k be a food group and I_k be the set of items listed under the food group k. We define the set of food groups as G (and $k \in G$). D_k is the per-capita daily calorie intake of food group k, as defined by the diet $\mathbf{D}$. We represent the food supply data for an item j in i at t as $f_j^{i,t}$. Then, the per-capita calorie intake of an item $j \in I_k$, in i at t, $d_j^{i,t}$, can be evaluated as the following:

$$d_j^{i,t} = D_k \cdot (f_j^{i,t} / \sum_{j \in I_k} f_j^{i,t}) \tag{1.2}$$

The units of $d_j^{i,t}$ are in kcals/capita/day. The units of $f_j^{i,t}$ are in tonnes. If the food supply quantity of an item j in i at t be represented as $s_j^{i,t}$, then the kilocalorie to kilogram conversion factor in i at t, $c_j^{i,t}$, can be evaluated as follows:

$$c_j^{i,t} = \frac{s_j^{i,t}}{f_j^{i,t}}$$

The unit of $c_j^{i,t}$ is kcals per kilogram. Unit of $s_j^{i,t}$ is in kcals (per capita per day). The yearly mass demand, $R_j^{i,t}$ of item j in i at t, in tonnes, would then be:

$$R_j^{i,t} = d_j^{i,t} \cdot P^{i,t} \cdot 365 \cdot \frac{c_j^{i,t}}{1000} \tag{1.3}$$

Where $P^{i,t}$ is the population of the country i in year t. Note that here I have made the following assumption: for any arbitrary dietary intake of a food group k (say D_k), the distribution of D_k across the group items maintains the same proportion to that of the reported data. That is, if the average caloric intake of bovine meat in USA in 1980 was $1/4^{th}$ of the total calorie intake of meats (let's say 500 kcals/capita/day), then any other dietary intake, D_k, for meats, would have $1/4^{th}$ of it dedicated to bovine meat (in USA, in 1980).

Now, I define another conversion factor C_j called the source conversion factor for a food item j. The source conversion factor is independent of the country or the year (hence it does not have the superscripts i and t). A source conversion factor converts the mass of a food item to an equivalent mass of its source item. For most items this conversion factor is 1. However, for items like beer, wine, butter etc, the value is not unity. For example, source of beer is barley and its mass conversion factor is 4.78. To generate 1 tonne of beer, 4.78 tonnes of barley is required, on average.

The food balance sheet reports data for the Domestic Supply Quantity (in tonnes) and the Import Quantity (in tonnes) of every food item j into a country i at a year t.

The Import Quantity data element, $I_j^{i,t}$, indicates the amount of the food item j that was imported into i in year t. The Domestic Supply Quantity data element, $D_j^{i,t}$, indicates the amount of j that is available to the population of i at t for domestic utilization. The ratio of Import Quantity to Domestic Supply Quantity is defined as the import dependency ratio, IDR, of j in i at t - $IDR_j^{i,t}$. That is,

$$IDR_j^{i,t} = I_j^{i,t} / D_j^{i,t}$$

Since both $I_j^{i,t}$ and $D_j^{i,t}$ are in tonnes, $IDR_j^{i,t}$ is unitless. The quantity j's source that comes in through import to meet the dietary demand of i at t is then,

$$I_{j,F}^{i,t} = \frac{IDR_j^{i,t} R_j^{i,t}}{C_j}$$

Similarly, the quantity j's source that comes from within the borders of i to meet the dietary demand of i at t is given by:

$$D_{j,F}^{i,t} = \frac{(1 - IDR_j^{i,t}) \cdot R_j^{i,t}}{C_j}$$

The units of $D_{j,F}^{i,t}$ and $I_{j,F}^{i,t}$ are in tonnes (per year). $Y_j^{i,t}$ and $\bar{Y_j}^t$ are defined as the yield of source of j in i and the average yield of source of j in the world respectively in t. Methods for calculating these are shown in the next subsection. The units of these variables are in tonnes per hectare. Then, the expected land required globally to produce the demand for item j in i at t (in hectares) is:

$$L_j^{i,t} = \frac{D_{j,F}^{i,t}}{Y_j^{i,t}} + \frac{I_{j,F}^{i,t}}{\bar{Y_j}^t} \tag{1.4}$$

Here, yield of i is factored in while calculating the global average yield $\bar{Y}_j^t$. The total global land required to produce the average dietary demand $\mathbf{D}$ for a country i in t is:

$$L^{i,t} = \sum_{k \in G} \sum_{j \in I_k} L_j^{i,t} \tag{1.5}$$

Yield calculation for non livestock item

Here I describe the method that calculates the variable $Y_j^{i,t}$ from data. $Y_j^{i,t}$ is the yield of source of j in i at t. The variable $\bar{Y}_j^{\,t}$ is $Y_j^{i,t}$ averaged over all i (all countries covered in the Food Balance Sheet).

I categorize seven items in the food balance sheet as livestock items. These are bovine meat, mutton & goat meat, pig meat, poultry meat, eggs, butter and milk. I represent the set of livestock items as LST. If $j \notin LST$, yield calculation is fairly simple:

$$Y_j^{i,t} = \frac{P_j^{i,t}}{A_{i,t}^j} \tag{1.6}$$

Where $P_j^{i,t}$ is the data for the quantity of j produced in i at t (in tonnes) and $A_{i,t}^j$ is the data for the area of land used to produce j in i at t (in hectares). These data elements are available from the Crops data sheet in the UN FAOSTAT database. Calculation of yield becomes complex when $j \in LST$. Yield units are in tonnes per hectare.

1.5.2 Yield calculation for livestock item

The idea behind livestock yield calculation is similar to the idea behind yield calculation for non-livestock items. To calculate yield of a livestock product j for a geographical region i, effective production of j and effective land used in i for j's production need to be calculated precisely. This is a complicated procedure. In the following two sub-subsections, I have described the procedure to perform this calculation. Methods for livestock yield presented here (i.e the next two sub-subsections) are partly paraphrased from the Supplementary Information document of Rizvi et al. [78]. Availability of newer data elements in FAOSTAT has facilitated changes in the model (relative to its first version in [78]). The changes incorporated by me have been included in the description here (replacing their earlier counterpart).

Livestock item production calculation: pasture and mixed/landless systems of production

For every livestock item $j \in LST$, a net production value (in tonnes) can be calculated using the data provided in the Livestock Primary datasheet of the UN FAOSTAT. For every livestock item, j in i at t, the Livestock Primary datasheet reports data for production (P), import (I) and export (E) of that item in (into/from) i at t. Net production is calculated by adding export and subtracting import from the production data value. That is, net production NP of a livestock item j in i at t is:

$$NP_j = P_j + E_j - I_j$$

The data for production (P) accounts for production for domestic consumption. For the remainder of this section I omit the superscripts i and t from the variables for the purpose of simplicity. It is always implied that calculations are being done for a country i at a year t.

For calculating yield, it is not enough to calculate net production of a livestock item j in i at t. Calculations need to be done to determine how much of the net production was obtained from a pasture system (NP_j^P) and how much of it was obtained from a mixed/landless system (NP_j^{ML}). Pasture and mixed/landless are two primary systems of livestock production. Pasture system produces livestock items from animals that feed off pasture while mixed/landless system produces livestock items from animals that feed off crop by-products, seed and feed. The calculation for breaking down net production into pasture and mixed/landless systems is performed by taking region estimates of production system division that were reported in [13]. For a geopolitical region R (e.g South Asia), Bowman et al. [13] estimates the fraction of livestock production in the two systems for the years 1970, 1995 and 2030. We use quadratic interpolation to obtain the value of these fractions for all years between 1961 and 2013. Once the calculation for net production is successfully done for an item j in country i at t, the production system division fraction for j in the region of i at t is estimated using quadratic interpolation on the Bowman et al. estimates. Using the interpolated value, net production is then broken down into - i) Net production in pasture system (NP_j^P), and ii) Net production in mixed/landless system (N_j^{ML}). All units of production are in tonnes.

Land area used for livestock item production

Land used to produce livestock product is divided into two parts: pasture area and cropland used to produce feed.

Ruminant livestock like cattle and sheep require pasture for their production. Data for total pasture area A_p used for agricultural production is provided by the Land Use data sheet of the UN FAOSTAT. If no such data is found for a particular country at a given year, we assume that pasture land is 69 % of country's agricultural land (the global average). Pasture land is further divided into two parts - pasture area in pastoral system, $A^{(P)}$, and pasture area in mixed/landless system, $A^{(ML)}$. This calculation is again done by performing quadratic interpolation on the region-wise grassland area estimates provided in Bowman et al. [13].

For every country reported in the FAOSTAT's Livestock Primary datasheet, data is available for its stock amounts (number of animals under each category that do not produce dairy or eggs). All categories of animals listed here can be mapped to a Food Balance Sheet animal product j. These stock data can be further segregated into 'number of stocks grown in pastoral system' and 'number of stocks grown in mixed/landless system' using stock division estimates provided in Bowman et al. [13]. If animal categories are indexed with k, then, I denote stocks of k with U_k and its segregation into pastoral and mixed/landless as $U_k^{(P)}$ and $U_k^{(ML)}$ respectively. The data for region estimates of stocks are also available from FAOSTAT's Live Animals datasheet. Stocks are unit less. They are reported in the data sheet as number of heads.

Pasture area in the pastoral and mixed/landless system assigned to k's rearing can hence be calculated as:

$$A_k^{(P)} = A^{(P)} U_k^{(P)} / \sum_k U_k^{(P)} \tag{1.7}$$

$$A_k^{(ML)} = A^{(ML)} U_k^{(ML)} / \sum_k U_k^{(ML)} \tag{1.8}$$

respectively.

Cropland area used for feed

Ruminant (cows, sheep and goat) and non-ruminant livestock (pigs and chickens) consume feed which composes of grasses, crop residues and food crops. We do not consider grasses and crop residue while calculating land equivalent of feed because they have already been accounted for earlier (grasses as pasture area and crop residue while calculating yield for non livestock items). Hence, in the calculation of cropland used for feed we are only concerned about the land used to produce the food crops that directly end up as the feed for livestock animals.

In this context, feed conversion ratio is an important concept. Feed conversion ratio is defined as the conversion factor between units of dry feed matter and units of animal product produced by it. For example, the answer to the question "How much beef does 1 tonne of corn produce?" is the feed conversion factor between corn and bovine meat. Estimates for feed conversion factor are, again, available from the Bowman et al. estimates [13]. Using quadratic interpolation, sub-continent level feed conversion rate r_k^f can be attained for an animal product corresponding to k at a year t between 1961 and 2013. Bowman et al. also provides estimates of the proportion of feed f_k represented by food crops for a given animal product. The proportion p_j of total available feed quantity assigned to production of animal product j, derived from animal k can be evaluated as follows:

$$p_j = \frac{NP_j^{(ML)} f_k r_k^f}{\sum_k NP_j^{(ML)} f_k r_k^f} \tag{1.9}$$

The FAOSTAT Crops data sheet reports for every crop the percentage assigned to feed. For a crop labeled as l we denote this fraction as Q_l. From the data for a country's import I_l, export E_l and production P_l of crop l, it is possible to calculate the self-sufficiency ratio of a country for the crop l, s_l, as follows:

$$s_l = \frac{P_l}{P_l + E_l - I_l} \tag{1.10}$$

Using the definitions of self sufficiency ratio (Equation 1.10), Q_l and p_j (Equation 1.9), it is possible to calculate the quantity of feed of crop l assigned to produce animal product j, q_{jl}, as:

$$q_{jl} = p_j s_l Q_l$$

Note that the factor s_j assures that land equivalent of imported feed is not factored in the calculation of yield of an animal product j in a country i. Crop yield of l, Y_l (estimated using Equation 1.6), is then used to calculate the amount of land spent as cropland area for generating feed for livestock animals. This is given by:

$$A_{jl}^{(C)} = q_{jl}/Y_l \tag{1.11}$$

Yield calculation of livestock items

Calculating the yield, Y_j, of a livestock item j is now possible with the equations 1.7, 1.8 and 1.11. It can be evaluated using the following expression:

$$Y_j = \frac{NP_j^{(P)} + NP_j^{(ML)}}{\sum_l A_{jl}^{(C)} + A_j^{(P)} + A_j^{(ML)}} \tag{1.12}$$

During calculation of yield, it is possible that a data element for an item in a country at a year is missing. In that case, the model fills up the hole in data with the data from the previous or the next year. Preference is given to filling up the data hole with the data from the previous year. If data is not available for either the previous or the next year, the model sets the value of that data element with that of the regional average.

This method for calculating land use eliminates the land equivalent of food wastage from its calculation. Only the land equivalent of consumed food is evaluated. The novelty of this method lies in calculating an estimate for the land used due to actual consumption by a country's population. The country-level land use data reported by the UN FAOSTAT in its Land Use data sheet accounts for the area of land inside a country's border that is used for the purpose of agriculture. Since countries are not completely self-dependent in generating their national food demand (since food items are traded with trade partners), the FAOSTAT data is not sufficient in estimating the land demand of the population of a country. Agricultural land in country i could be partly serving the demands of country j and vice versa. Additionally, since the Land Use data sheet reports raw land cover data, it does not segregate the reported land use value into land equivalent of consumption and land equivalent of food wastage.

1.5.3 Examples of calculating land use from dietary consumption

Here I demonstrate the model described in the previous subsection with some examples.

First Example

In the first example, we calculate land equivalent of two diets that were constructed in Table 1.2. Land use results for dietary construction of Canada and India are shown in Table 1.3. Land equivalent of each food group consumption is shown and broken down into two categories - i) local and ii) remote. The 'local' land accounts for the area of agricultural land spent inside the border of the country to generate the corresponding food group demand. The 'remote' land value accounts for the area of agricultural land spent

Food group	Land use, 2013 (million hectares)					
	Canada			India		
	local	remote	total	local	remote	total
Fruits	0.023	0.404	0.427	5.837	0.052	5.890
Vegetables	0.199	0.189	0.388	9.617	0.008	9.626
Grains	0.993	0.137	1.131	63.720	0.035	63.755
Meats (and Pulses)	10.635	7.435	18.070	59.801	4.123	63.925
Dairy	0.250	0.026	0.276	2.619	0.001	2.620
Oils	3.427	2.630	6.057	71.746	47.514	119.261
Sugar	0.0003	0.759	0.759	4.796	0.341	5.137
Total	15.530	11.582	27.112	218.140	52.076	270.216

Table 1.3: Demonstration of land use evaluation model with an example - local, remote and total land used for the average dietary consumption of Canada and India for the year 2013.

outside the country. Adding them up gives the 'total' land required globally to generate the food group demand for the country.

Land use results in Table 1.3 indicate that the average land use of India is way higher than that of Canada. Secondly, India is comparatively more self sufficient in generating its own demand compared to Canada. For India, approximately 80% of its total land use is local. Whereas, for Canada it is 45% of its total land use. The evaluated numbers for India and Canada are vastly different because of their population difference in 2013. In 2013, Canada had 35.08 million residents whereas India had 1.28 billion residents (36.5 times).

Second example

In the second example, I use the FAOSTAT's Food Balance Sheet data to construct the average diets of USA, Brazil, China and India for every year between 1961 and 2013. An example of such a construction is shown in Table 1.2. Then, using the model described in the previous subsection, I calculate the amount of land used by these countries, globally, for their demand over the aforementioned time period. The results are shown in Figure 1.4.

China and India have comparable per capita land use whereas USA and Brazil have comparable per capita land use. Although the average per capita land use of China and India is almost a hectare lower than USA and Brazil, their total land use is comparable due to vast differences in population. The observable decline in per capita land use, seen

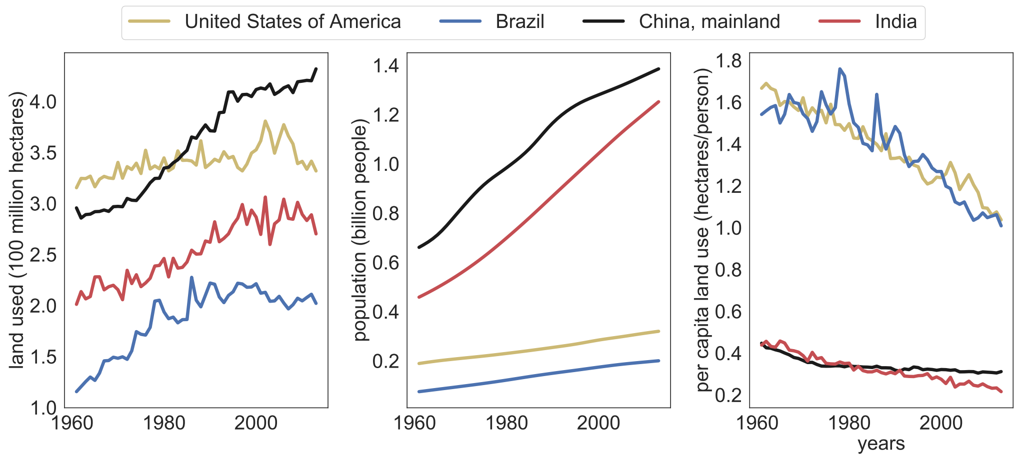

Figure 1.4: Demonstration of the land use evaluation model - agricultural land used, population and per capita land use of USA, China, Brazil and India from 1961 to 2013. Agricultural land use is calculated using the method described in Section 1.5.1

for all the countries between 1961 to 2013, is attributed to growth in global yields of crops in the last 60 years. Although per capita land use has decreased, total land use of countries have increased due to population increase outweighing the effect of decreasing per capita land use.

Third example

In the third example, I calculate the land equivalent of a hypothetical diet in order to assess its land footprint. In this example, I assume that the entire world consumes the 2010 USDA recommended diet from 1961 to 2013. I have previously introduced the 2010 USDA dietary recommendation in Section 1.4. Results are shown in Figure 1.5.

In Figure 1.5 I have plotted land spared versus years. Land spared due to a diet $\mathbf{D}$ at a year t is defined as follows:

$$\text{Land Spared}_{\mathbf{D}}^{t} = \text{Land actually used at } t - \text{Land used if the globe consumed } \mathbf{D} \text{ at t} \tag{1.13}$$

At 2013, the value of total land spared is -811 million hectares (see 'all groups' in Figure 1.5). That is, if the global population consumed the 2010 USDA dietary recommendation

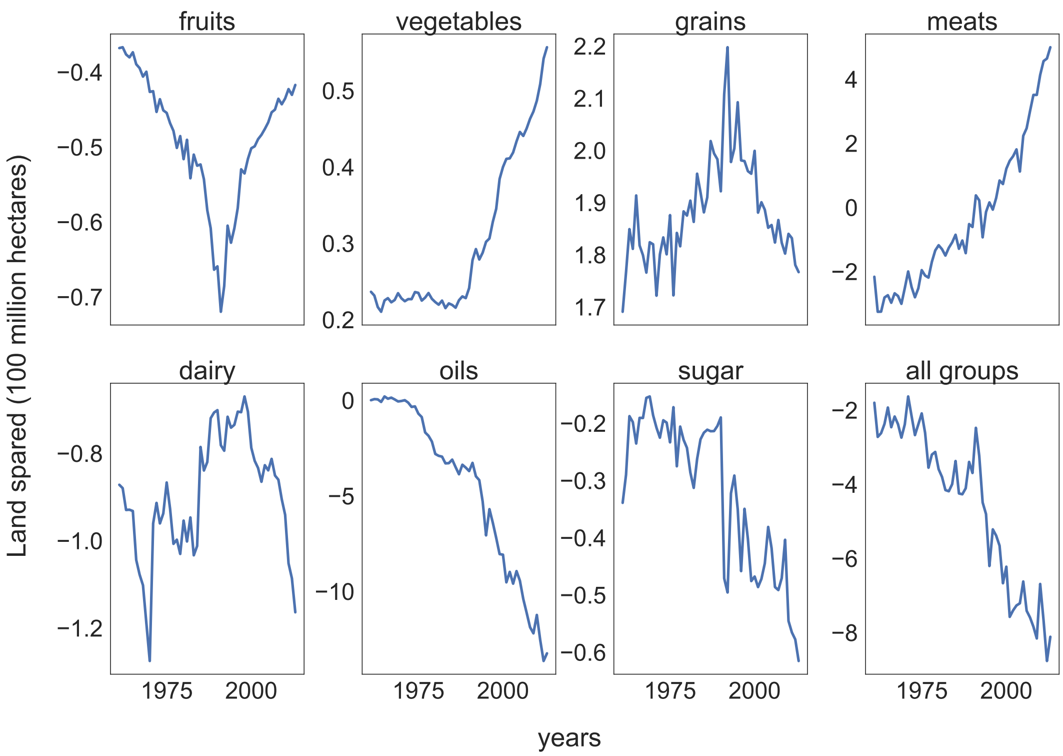

Figure 1.5: Land spared if the global population adopted the 2010 USDA dietary recommendation from 1961 to 2013. Plots show model output of amount of land spared if the global population adopted the recommended diet for all years between 1961 and 2013. Land spared is broken down food group-wise.

in 2013, an additional 811 million hectares of land would have been required to generate the extra demand. The USDA dietary recommendation, although nutritionally sound, is not ecologically sustainable for global adoption.

Fourth example

This example follows directly from the third example. Similar to the previous example, we construct hypothetical diets and find their corresponding land equivalent values. We make deviations from the USDA dietary recommendation in the groups of Meats, Grains and

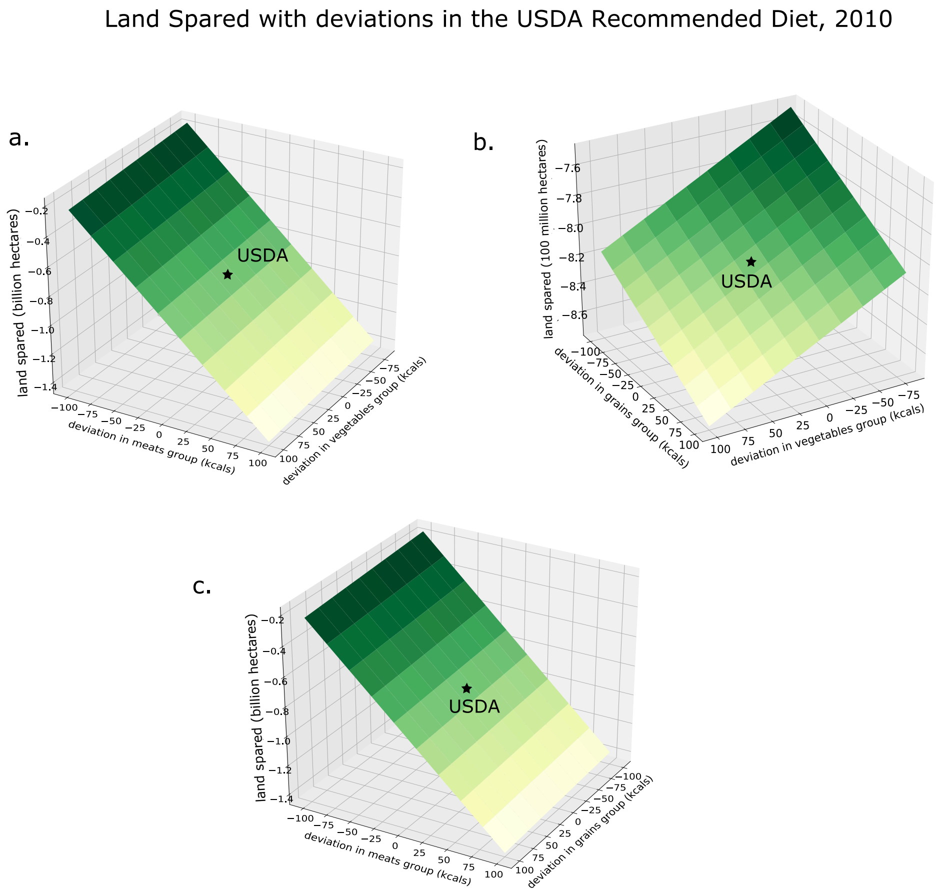

Figure 1.6: Land spared if the global population adopts a diet that is deviated from the 2010 USDA dietary recommendation. Deviations are made pairwise in the groups of meats, grains and vegetables. **a.** In this figure, land spared is plotted with deviations in the groups of meats and vegetables. Group calorie of grains remains at the recommended level **b.** Deviations are made to the groups of grains and vegetables while meats calories is affixed at the recommended level **c.** Deviations are made to groups of meats and grains while keeping vegetable calories fixed at USDA recommended level. The black star represents the USDA recommended diet (no deviation). Land spared at 2013 due to global USDA diet adoption is -811 million hectares.

Vegetables to observe the corresponding effect on global land spared. We only show results for the year 2013. For every deviated diet, global land spared at 2013 is evaluated and plotted in Figure 1.6. We make pairwise deviations among the three groups while keeping the third group fixed at the USDA recommended level. To observe results, I have made deviations of -100 kcals to 100 kcals from the recommended level in each group.

Among the three groups deviated, the group of ‘meats’ affects global land use the most. A reduction of 100 kcals per capita per day in the food group of ‘meats’ (relative to the USDA recommendation) saves approximately 600 million hectares globally. On the other hand, deviations in the groups of ‘vegetables’ and ‘grains’ show a lesser impact on global land use. Reducing 100 kcals/capita/day in both of them results in a reduction of about 40 million hectares globally.

This example shows the land-intensive characteristic of a meat intensive diet. If an individual shuns a hundred kilocalories from their daily diet of meats and replaces it with twice the amount of calories from grains and vegetables, they still contribute towards saving land globally.

1.6 Future socio-economic scenarios in the literature

In this section, the Shared Socio-Economic Pathway (SSP) scenarios are introduced and discussed. We use these scenarios extensively in the second chapter. A basic overview of them is provided in this section.

1.6.1 The IPCC and its assessment reports

The IPCC (Intergovernmental Panel on Climate Change) is an intergovernmental body of the United Nations that releases reports that cover “scientific technical and socio-economic information relevant to understanding the scientific basis of risk of human-induced climate change, its potential impacts and options for adaptation and mitigation”. This description of the IPCC is provided by the UN body itself in the document titled *Principles Governing IPCC Work* (approved at the 14^{th} IPCC Session in Vienna).

Instead of conducting any independent or original research, the body compiles published peer (and non peer) reviewed sources to create its assessment reports that contain guidelines for nations in the form of a *Summary for Policymakers* document. In its latest assessment report (the Fifth Assessment in 2018), it released the *Special Report on Global Warming of 1.5 °C*

Figure 1.7: The SSP scenarios mapped into the challenges to mitigation-adaptation space. Image taken from the Wikipedia page to Shared Socioeconomic Pathways. By Sfdiversity - Own work, CC BY-SA 4.0, link

1.6.2 The Shared Socioeconomic Pathway (SSP) scenarios

The Shared Socio Economic Pathway scenarios (SSP scenarios) are a list of five storyline scenarios constructed formally for producing the Sixth IPCC Assessment Report. These storyline narratives are constructed to describe future socio-economic developments of the world. Each storyline is unique in its adaptation and mitigation challenges (towards climate change). Every scenario has a unique country-level population and GDP projection till 2100. Figure 1.7 shows the map of these five scenarios in the adaptation-mitigation plane. Regional level population and income projections under five SSP scenarios till 2100 (starting from 2015) are shown in Appendix - Supplementary Figure B.11. The division methodology of regions are explained in Appendix Section A.5.2.

The SSP scenarios were first introduced in Riahi et al. [77]. Their storyline descriptions, presented below, are quoted directly from the original paper:

SSP1: Sustainability (Taking the Green Road)

"The world shifts gradually, but pervasively, toward a more sustainable path, emphasizing more inclusive development that respects perceived environmental boundaries. Management of the global commons slowly improves, educational and health investments accelerate the demographic transition, and the emphasis on economic growth shifts toward a broader emphasis on human well-being. Driven by an increasing commitment to achieving development goals, inequality is reduced both across and within countries. Consumption is oriented toward low material growth and lower resource and energy intensity." [77]

SSP2: Middle of the Road

"The world follows a path in which social, economic, and technological trends do not shift markedly from historical patterns. Development and income growth proceeds unevenly, with some countries making relatively good progress while others fall short of expectations. Global and national institutions work toward but make slow progress in achieving sustainable development goals. Environmental systems experience degradation, although there are some improvements and overall the intensity of resource and energy use declines. Global population growth is moderate and levels off in the second half of the century. Income inequality persists or improves only slowly and challenges to reducing vulnerability to societal and environmental changes remain." [77]

SSP3: Regional rivalry (A Rocky Road)

"A resurgent nationalism, concerns about competitiveness and security, and regional conflicts push countries to increasingly focus on domestic or, at most, regional issues. Policies shift over time to become increasingly oriented toward national and regional security issues. Countries focus on achieving energy and food security goals within their own regions at the expense of broader-based development. Investments in education and technological development decline. Economic development is slow, consumption is material-intensive, and inequalities persist or worsen over time. Population growth is low in industrialized and high in developing countries. A low international priority for addressing environmental concerns leads to strong environmental degradation in some regions." [77]

SSP4: Inequality (A Road Divided)

"Highly unequal investments in human capital, combined with increasing disparities in economic opportunity and political power, lead to increasing inequalities and stratification both across and within countries. Over time, a gap widens between an internationally-connected society that contributes to knowledge- and capital-intensive sectors of the global economy, and a fragmented collection of lower-income, poorly educated societies that work in a labor intensive, low-tech economy. Social cohesion degrades and conflict and unrest become increasingly common. Technology development is high in the high-tech economy and sectors. The globally connected energy sector diversifies, with investments in both carbon-intensive fuels like coal and unconventional oil, but also low-carbon energy sources. Environmental policies focus on local issues around middle and high income areas" [77]

SSP5: Fossil-Fueled Development (Taking the Highway)

"This world places increasing faith in competitive markets, innovation and participatory societies to produce rapid technological progress and development of human capital as the path to sustainable development. Global markets are increasingly integrated. There are also strong investments in health, education, and institutions to enhance human and social capital. At the same time, the push for economic and social development is coupled with the exploitation of abundant fossil fuel resources and the adoption of resource and energy intensive lifestyles around the world. All these factors lead to rapid growth of the global economy, while global population peaks and declines in the 21st century. Local environmental problems like air pollution are successfully managed. There is faith in the ability to effectively manage social and ecological systems, including by geo-engineering if necessary." [77]

In the second chapter, I use the SSP scenarios primarily for the purpose of using their country level population and income projections till 2100. Those act as inputs to the coupled human-land system model when I make projection for future land use. We also construct future yield scenarios (denoted by f scenarios) which are independent of the SSP scenarios. In an earlier paper [74], SSP storylines for future agricultural yield and consumption patterns were constructed. However, in my model I do not use these constructions. I show results for all possible yield scenarios under each SSP scenario.

1.7 Evolutionary game theory

Evolutionary game theory is often loosely defined as the application of the mathematical theory of games in the broad field of evolutionary biology. Game theory is believed to have begun in 1928 as a unique field after John von Neumann formalized some of the fundamental theorems of the literature in his paper *On the Theory of Games of Strategy*. In 1973, British mathematician Dr. John Maynard Smith formalized the concept of evolutionary

Payoff for Alice	If Bob plays		
If Alice plays		C	D
	C	R	S
	D	T	P

Table 1.4: Payoff matrix for a two player two strategy game between players Alice and Bob with strategies C and D.

game theory by bridging the gap between mathematical game theory and biological evolution. His paradigm shifting 1982 book titled *Evolution and the Theory of Games* drew in a lot of outside attention into game theory–a field that had, till then, only interested mathematicians and economists.

The fundamental concept behind evolutionary game theory is the idea that evolution of any sort, biological (changes in heritable characterstics with generations) or cultural (changes in beliefs and norms in society), is driven by the frequency distribution of competing agents in the population (genotypes in biological evolution and social strategies in cultural evolution). Frequency distribution of the agents endogenously determines the reproductive fitness landscape, which, in turn, drives the course of evolution.

In this section I provide a brief overview of the fundamentals of evolutionary game theory in order to set up the evolutionary game theory inspired imitation dynamics model in the next chapter.

1.7.1 Fundamentals of game theory: two players, two strategies

In a *game* between Alice and Bob with two possible strategies, four deterministic outcomes exist. Let us represent the two strategies that they can play as C and D. Since strategies in game theory are mutually exclusive of each other by definition, strategies in the two strategy game are also termed as co-operation (C) and defection (D).

Each of the four outcomes has an associated payoff for both the players. These outcomes can be represented in the form a *payoff matrix* (see Table 1.4). Entries of the payoff matrix (P, R, S, T) essentially define the characteristic of the game and also its outcome if players are assumed to be rational and in possession of complete knowledge about the game. A *pure strategy* game is defined as a game where players can play either one of the two strategies. Its counterpart, the *mixed strategy* game, is a game where players play their strategies probabilistically.

Prisoner's Dilemma

Prisoner's dilemma is the most popular game in the literature of game theory. A two player, two strategy game is called a Prisoner's Dilemma when $T > R > P > S$. Being the sole defector has the highest payoff. Payoff for co-operating with co-player is second highest followed by the payoff for defecting against the co-player. Being the sole co-operator has the lowest payoff. An example of the Prisoner's Dilemma game is the donation game where a benefit b is provided to the co-player at a cost c ($b > c$). In that game, $R = b - c$, $S = -c$, $T = b$ and $P = 0$.

The Hawk and Dove game

The hawk and dove game is the most popular game in the literature of evolutionary game theory. In this game, players have the choice to either be the *hawk* or the *dove*. The *dove* strategy is analogous to co-operation whereas the *hawk* strategy is analogous to defection. Doves are conflict-avoiding whereas hawks are conflict-seekers. When fighting over a reward V, two doves agree to share the spoils equally without conflict. Two hawks fight over the reward and while doing so they each expend an effort $d/2$ ($d > V$). When a hawk encounters a dove, it wins the total reward by force. Let us denote the *hawk* strategy as D and the *dove* strategy as C. For the hawk and dove game, $R = V/2$, $S = 0$, $T = V$, $P = V/2 - d/2$. For the hawk and dove game, the ordering of the payoffs is hence: $T > R > S > P$. If the reward V were higher than the cost d, the game would have been a Prisoner's Dilemma.

Every non co-operative game has a fixed solution called the *Nash equilibrium*. A Nash equilibrium is a solution where no player can gain anything by changing only their own strategy. For a given game, a Nash equilibrium can either be a set of pure strategies or a set of mixed strategies. For example, in Prisoner's Dilemma, both players defecting is the Nash equilibrium (one cannot increase their payoff by changing only their strategy from defect-defect). Whereas, for the hawk and dove game, the Nash Equilibrium is a mixed strategy.

If mixed strategies are allowed, every game with finite number of players and finite number of pure strategies has a Nash equilibrium (the Nash existence theorem).

1.7.2 Population dynamics and evolutionary games

Let us assume that there are two viable strategies, C and D, for a population. Every agent in the population possesses one of the two strategies. I represent the fitness of the two strategies as f_C and f_D. Here the term fitness is used in the Darwinian sense. That is, a higher fitness strategy will have a higher reproductive success compared to a lower fitness strategy. Let us suppose that the frequency (relative abundance) of strategy C in the population is represented as x_C and the frequency of strategy D in the population is represented as x_D. Naturally, $x_C + x_D = 1$. Average fitness of the strategies in the population is, hence:

$$\bar{f} = x_C f_C + x_D f_D \tag{1.14}$$

If total population is sufficiently large and generations continuously blend into each other, it can be assumed that $\mathbf{x} = (x_C, x_D)$ evolves in the simplex, S_2, as a continuous differentiable function of t. The rate of increase of a strategy $i \in \{C, D\}$ is a measure of its evolutionary success. By Darwinian principles, evolutionary success is measured by the difference between fitness and average fitness of the population. Then, by that principle, rate of increase of strategy i's abundance in a population can be expressed as:

$$\frac{\dot{x}_i}{x_i} = \text{fitness of i} - \text{average fitness for all} \quad j \in \{C, D\}$$

That is,

$$\dot{x}_i = x_i(f_i - \bar{f}) \tag{1.15}$$

Using Equations 1.14, 1.15 and the fact that $x_C + x_D = 1$, the rate of increase of strategy C's frequency in the population can be simplified into:

$$\dot{x}_C = x_C(1 - x_C)(f_C - f_D) \tag{1.16}$$

Since $\dot{x}_D = -\dot{x}_C$, rate of increase of strategy D's frequency in the population can be expressed as:

$$\dot{x}_D = x_D(1 - x_D)(f_D - f_C) \tag{1.17}$$

The same theory applies for n strategies in a population. In that case, the frequency vector $\mathbf{x}$ is restricted to the simplex S_n instead of S_2. In the literature of evolutionary dynamics, Equations 1.16 and 1.17 are more popularly known as replicator equations.

Absolute natural selection

The regime of absolute natural selection exists when one strategy always possess higher fitness than the other ($f_C > f_D$ or $f_D > f_C$). Irrespective of the initial condition, the population always converges to a single strategy. The other competing strategy is wiped out.

Frequency dependent selection, evolutionary game theory

The field of evolutionary game theory deals with replicator equations that have frequency dependent fitness. This means that f_C and f_D are functions of $\mathbf{x} = (x_C, x_D)$.

Since strategies with higher payoff replicate faster, fitness of strategies are equated to their average payoff. Let us assume that strategies C and D pertain to the game defined in Table 1.4. If relative abundance of C and D strategy holders in the population are x_C and x_D respectively, the effective payoff of C (and hence its fitness) is:

$$f_C = x_C R + x_D S$$

Similarly, effective payoff of D (and hence D's fitness) is:

$$f_D = x_C T + x_D P$$

Using these fitness definitions and Equation 1.16, it is possible to write:

$$\dot{x}_C = x_C(1 - x_C)(x_C(R - T) + x_D(S - P)) \tag{1.18}$$

An assumption of well mixed population is made here. That is, the probability of encountering a strategy holder i is directly proportional to the relative abundance of i in the population. The following can be inferred about the simple evolutionary dynamics that I just defined (Equation 1.18) [64]:

1. When $R > T$ and $S > P$, C always dominates over D. Given any initial distribution of C and D in the population, the population always converges to all C (regime of absolute natural selection).

2. Similarly if $R < T$ and $S < P$, D absolutely dominates over C (regime of absolute natural selection).

3. if $R > T$ and $S < P$, the system is bi-stable. Depending upon the initial condition, only one strategy can survive (while the other one is wiped out).

4. if $R < T$ and $S > P$, strategies can co-exist together in the population.

5. if $R = T$ and $S = P$, the system is neutral. Any initial configuration is maintained throughout.

For conditions 3 and 4 in the above list, the equilibrium value of x_C is

$$x_C^* = \frac{P - S}{R - S - T + P}$$

.

For condition 3, if $x_C(0) > x_C^*$, then, $x_C(t) = 1$, eventually, for t greater than some t_0. Oppositely, for the same condition, if $x_C(0) < x_C^*$, then, $x_C(t) = 0$ for t greater than some t_0. The dynamics is termed bi-stable when it shows these properties. The final state of the population is either all C or all D depending upon the initial condition.

For condition 4, irrespective of $x_C(0)$ ($0 < x_C(0) < 1$), $x_C(t) = x_C^*$, eventually, for t greater than some t_0. If $x_C(0)$ is 0 or 1, it does not change for any $t \in [0, \infty)$. This dynamical behaviour is termed as 'co-existing'. C and D strategies can co-exist together in the population at a game-determined equilibrium, x_C^*.

For condition 5, $x_C(t) = x_C(0)$ for $t \in [0, \infty)$. Strategies C and D are said to be in neutral equilibrium. The initial configuration is never disturbed.

If the Prisoner's Dilemma game is played in a population, condition 2 applies (since for Prisoner's Dilemma, $R < T$ and $S < P$). Irrespective of the initial condition, the final state of the population is all D. However, if Hawk and Dove is played in the population, $P < S$ (as $V/2 - C/2 < 0$) and $R < T$. For this case, condition 4 applies. Hawks and doves can co-exist in the population at a game-determined equilibrium.

Social learning rate

An extension of the replicator dynamics can be the case where individuals do not sample the population with absolute certainty. While deriving the model, it was assumed that individuals always encounter either similar strategies or opposite strategies while randomly sampling their population. It could also be possible that they do not choose to interact within their population (by refusing to sample). This behaviour can be captured by a parameter called the social learning rate which is nothing but the sampling rate of individuals in their population. The social learning rate is a parameter that can vary between 0 to 1. A lower value of this parameter indicates lesser velocity for the motion of $\mathbf{x}$ in the simplex. If κ is used to represent the social learning rate, equations 1.16 and 1.17 can be modified into:

$$\dot{x}_C = \kappa x_C(1 - x_C)(f_C - f_D)$$

and,

$$\dot{x}_D = \kappa x_D(1 - x_D)(f_D - f_C)$$

In evolutionary game theory, fitness is always modeled as a linear function of payoff. Any differentiable function can be used for modeling the relationship between payoff and fitness as long as it is monotonically increasing with payoff.

1.7.3 Using replicator dynamics to model imitation of behaviours

When there are two strategies viable to the population, their effective payoff difference determines the course of evolution for their sub-populations. This evolutionary dynamics, also termed as imitation dynamics (formally replicator equation), has been widely used in modeling human behaviour in social settings [42, 7, 16, 46].

In [7], imitation dynamics is used to model the evolution of vaccinators and non-vaccinators in a population. In that model, fitness of vaccinators increases with decrease in perceived probability of significant morbidity from the vaccine. For non vaccinators, fitness depends upon perceived probability of suffering significant morbidity upon infection and the probability of eventually getting infected. In [16], imitation dynamics is used to model evolution of mitigators and non-mitigators of climate change in a population. Fitness of the sub-populations depend upon utility functions governed by costs of climate change mitigation, costs imposed on non-mitigative behaviour and costs associated with average global temperature anomaly. The model also accounts for costs associated with social norms that strengthen the majority behaviour. In [46], imitation dynamics is used to study the evolution of grassland preferrer and forests preferrers in a population. Their evolution governs the stability of forest-grassland mosaic ecosystems. In the second chapter, I introduce an evolutionary game theory styled model to describe the evolution of practitioners and non- practitioners of sustainable diets in a population.

1.8 Objectives and Direction

Thus far in this thesis I have discussed: the history of global agricultural land use (Section 1.1), impact of agricultural expansion on environment and ecosystem (Section 1.2), drivers of agricultural land use (Section 1.3), a model for mapping an average diet of a population to an equivalent area of land (Section 1.5.1), socio-economic scenarios of the future (Section 1.6) and replicator dynamics in evolutionary game theory (Section 1.7).

All of these sections set up the second chapter of this thesis. In the second chapter, the role of sustainable diets in influencing global agricultural land use is studied using an evolutionary game theory inspired imitation dynamics model. Because sustainable consumption is ultimately an individual level choice, driven by socio-economic factors, a game theoretical approach to modelling the decision making assures that the problem is addressed using first principles.

The next chapter is presented in the form of a manuscript in progress. The individual level consumption model presented in the next chapter takes into account the economic and social barriers of adopting a sustainable diet. Using the country-level model, projections for global land use are made till 2100, under multiple socio-economic scenarios (described in Section 1.6). Additionally, using the model, I demonstrate the mitigating power of social parameters that possess the potential to accelerate or decelerate global migration towards sustainable consumption.

Earlier studies have explored the strong mitigating effect of reduced consumption levels on climate and global land use [74, 92, 75, 88]. However, in these studies, diet is considered exogenous to the system. Dietary patterns are treated as scenarios. Projections of land use (or emissions) are made under each scenario of future consumption pattern. For example, in [74, 92], future dietary consumption scenarios of 'No ruminant meat', 'No meat', 'No animal product' and 'Healthy Diet' are constructed to observe the corresponding model projections of land use and global emissions. The scenario description of 'No Ruminant Meat' in [92] goes as follows:

"As reference but with complete substitution of proteins from ruminant meat (cattle, buffaloes, sheep and goats) by plant proteins starting in 2010 and completed by 2030. By-products such wool and leather are also assumed to be substituted by other materials."

Although the projections from these models are widely accepted in the literature, they provide little or no insight into understanding how these variants of diets can actually evolve within populations. Dietary change is not a sudden change that gets implemented over a day. Unlike industrial emissions, it cannot be controlled with regulations and taxation. Dietary change is a slow behavioural process that evolves gradually with time. Various social, cultural, economical and health related causes affect dietary behaviour. The model in chapter two, albeit simplistic, provides a foundation for studying the socio-cultural mechanisms that drive changes in dietary behaviour.

Chapter 2

Global land use and the future of sustainable consumption: projections of a coupled social-land use model[1]

[1]This chapter is based on the paper in progress: Saptarshi Pal, Chris T. Bauch, Madhur Anand. Future of Global Land Use and Sustainable Consumption with a Social Learning Model. *In Progress, 2020*

2.1 Abstract

Among the complex determinants of global agricultural land use, dietary patterns have been identified as a key factor. Models that project future land use often assume fixed scenarios for how sustainable dietary patterns will change over time, but land use is itself a driver of dietary decision-making and thus it responds to changing land use. Our coupled socio-land-use model captures both endogenous drivers (behaviours evolving through social learning) and exogenous drivers (behaviours evolving due to perceived ecological cost of land expansion) of dietary behaviour. We make global land use projections until 2100 and explore social strategies of land sparing under multiple scenarios of population, income and growth in agricultural yield. The model exhibits synergistic effects between coupled socio-land use dynamics and socio-economic parameters like income elasticity. When future agricultural yields are low and/or population size is high, we find that coupled socio-land feedbacks can reduce the projected peak global land use on the order of 2 billion hectares, but only if socio-economic barriers to adopting a sustainable diet are sufficiently low. In contrast, when population growth is low or yield is high, global reductions in income elasticity of food purchase can increase peak land use on the order of 100 million hectares. We also comment on charting behavioural pathways to minimize peak land use in the 21st century. By providing insights into the potential role of coupled socio-land dynamics, our paper demonstrates the value of diversifying global land use modelling by accounting for coupled socio-land feedbacks.

2.2 Introduction

From 1961 to 2013 global food demand went up threefold, from 6.4 trillion to 19.4 trillion kilocalories (kcals) 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 kcals/day to 2600 kcals/day over this period [32]. Land is the primary global food supply. In 2013, an estimated land equivalent of 3.5 billion hectares was consumed (72% of agricultural land in that year) while approximately 1.4 billion hectares of land was spent on wasted food [78]. In the 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 21^{st} century. However, agricultural expansion and intensification represent major ecological threats, ranging from clearing of forests and habitat fragmentation [60, 14] to increased greenhouse has emissions [15, 101].

Agricultural intensification faces an uncertain future. From 1961 to 2013, production gains were mostly due to the steady rate of growth of productivity of land [15, 32]. Some studies suggest that certain major crops are approaching their yield ceilings in rich countries [31, 25, 18] indicating that further yield improvement will be unlikely in those countries. There has been a deceleration in yield rates across the globe primarily due to decreasing investment in agricultural research and reduced food production prices in both higher and lower income countries [69]. Slowing intensification may trigger agricultural land expansion to catch up with rapidly growing demand for food. We note that increasing yield is a necessary but not sufficient condition for land sparing, since it needs to be coupled with improved governance, planning and zoning to realize their sparing potential [55, 59].

Existing research on sustainable pathways of agricultural technologies [98, 39] tend to focus on the supply side of the problem. On the demand side, they assume simple scenarios that describe how future demand will change according to some trajectory that is independent of the complex drivers which actually determine agricultural land use. Sophisticated land system ensemble models that are used to project land use in IPCC reports do not explicitly study the dynamics of system-induced drivers of human consumption behaviours, since their models use scenarios for homogenized dietary consumption patterns as inputs [74, 92, 1, 88]. Although it is fairly well understood that dietary patterns can heavily influence trajectories of global land use [1, 93, 2, 83, 37], there has been limited investigation into how these shifts in dietary pattern can actually evolve within populations due to social and economic factors, and in particular how they respond to changing land use. Studies have found that individuals do factor in environmental factors while making dietary decisions [9, 48]. Sustainable dietary patterns, unlike industrial emissions, cannot be be regulated or enforced directly by changes in governmental policies. Sustainable consumption is an economically and socially induced process that evolves endogenously in a population and hence requires a more systematic study.

From the individual perspective, one cost of adopting a land sparing sustainable diet could be to give up the personal satisfaction of consuming meat [68, 30]. However, everyone benefits from an individual's choice to adopt a sustainable diet, since global land use is reduced as a result of that choice. 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 [41, 84]. Modeling social behavior in public goods games often uses models of imitation dynamics from evolutionary game theory, which captures how individuals learn behaviours from one another [7, 34, 10].

Mathematical models of sustainable food systems are becoming an increasing topic of research [63, 4, 87, 57, 90, 43]. More recently, interest has grown in coupling imitation dynamic models to models of natural processes [16, 8, 19]. Here, we introduce a modelling framework for coupling the country-level social dynamics of sustainable dietary decision-making under imitation dynamics 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 novel predictions that are not possible using standard approaches that ignore these coupled interactions, and (2) gain insight into how potential coupled social-land use processes alter both projected global land use and projected dietary trends. Our objective was not to generate a set of projections for policy use (although we do not rule out that future models could capture more complex social processes for policy applications). Hence, we opted for a minimal model that was easier to fit to data and gain insight from.

2.3 Model Overview

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

For every country, i, we define bounds for maximum and minimum per capita land use in year t ($c_i^{U,max}(t)$ and $c_i^S(t)$ respectively). We classify individuals as having either sustainable or unsustainable diets. Individuals with a sustainable diet consume $c_i^S(t)$ hectares per capita in year t. Those with unsustainable diets increase their consumption based on per capita income up to a maximum $c_i^{U,max}(t)$. We define h_i as the elasticity of food consumption with respect to income in country i (or just, income elasticity of food consumption in i). The higher h is, the more rapidly consumption changes with income for those practicing an unsustainable diet (see Methods). The calculation procedure for $c^{U,max}$ and c^S appears in Methods. Beyond 2013 (the last available year in the FAO food balance sheets), these bounds are extrapolated under different scenarios defined by a parameter f (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 assume every country i is characterized by a barrier to adopting a sustainable diet, σ_i, such that when global land use $L < \sigma_i$, the perceived costs of a sustainable diet push the population toward an unsustainable diet, while when $L > \sigma_i$, the population moves toward the sustainable diet. σ_i represents a barrier to achieving population-wide adoption of a sustainable diet due to the combined effects of various psychological, social and economic factors. The rate of dietary change is dictated by κ_i, which describes how fast social learning occurs in country i. κ_i is a control knob that determines how often an individuals samples other individuals in the population regarding their diet. If an individual on a non-sustainable diet samples an individual on a sustainable diet and if $L > \sigma_i$, they switch to a sustainable diet with a probability proportional to the difference $L - \sigma_i$. A similar process occurs for the switch from sustainable to unsustainable diets (see Methods). When $L > \sigma_i$, the proportion x of individuals on a sustainable diet increases as individuals switch from an unsustainable diet to a sustainable diet. The opposite happens in the unsustainable regime. A high value of κ_i can accelerate change in either direction depending on the difference between L and σ_i.

We use a previously published model [78] to generate country-level land use data based on dietary patterns from 1961 to 2013. We fit our model to these data to estimate κ_i, σ_i and h_i for 166 currently existing countries (see Appendix Section A.1 for methods of parameter estimation and Appendix Section A.4). 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). The model parameters, κ, h and f, are real numbers in the interval $(0, 1)$.

2.4 Results

We make global land use projections for 20 scenario combinations for the 164 countries we analyzed (see Appendix Section A.4 for details on countries used). For country-level population and income projections, we use the five shared socio-economic pathway (SSP) scenario markers, SSP1 to SSP5 [77, 26]. Each SSP scenario represents a unique storyline for the future that dictates the trajectory of population and income in countries (among other things). Although these scenarios have unique storylines for yield growth, we also show results for different possible future yield trajectories under each SSP scenario. SSP1 is characterized by relatively high income and small population. In SSP2, current trends of population and income continue, and moderate progress is made by achieving income convergence between countries. 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 high disparity in economic growth rates between high income and low income countries; global growth is less rapid compared to SSP1. In a 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

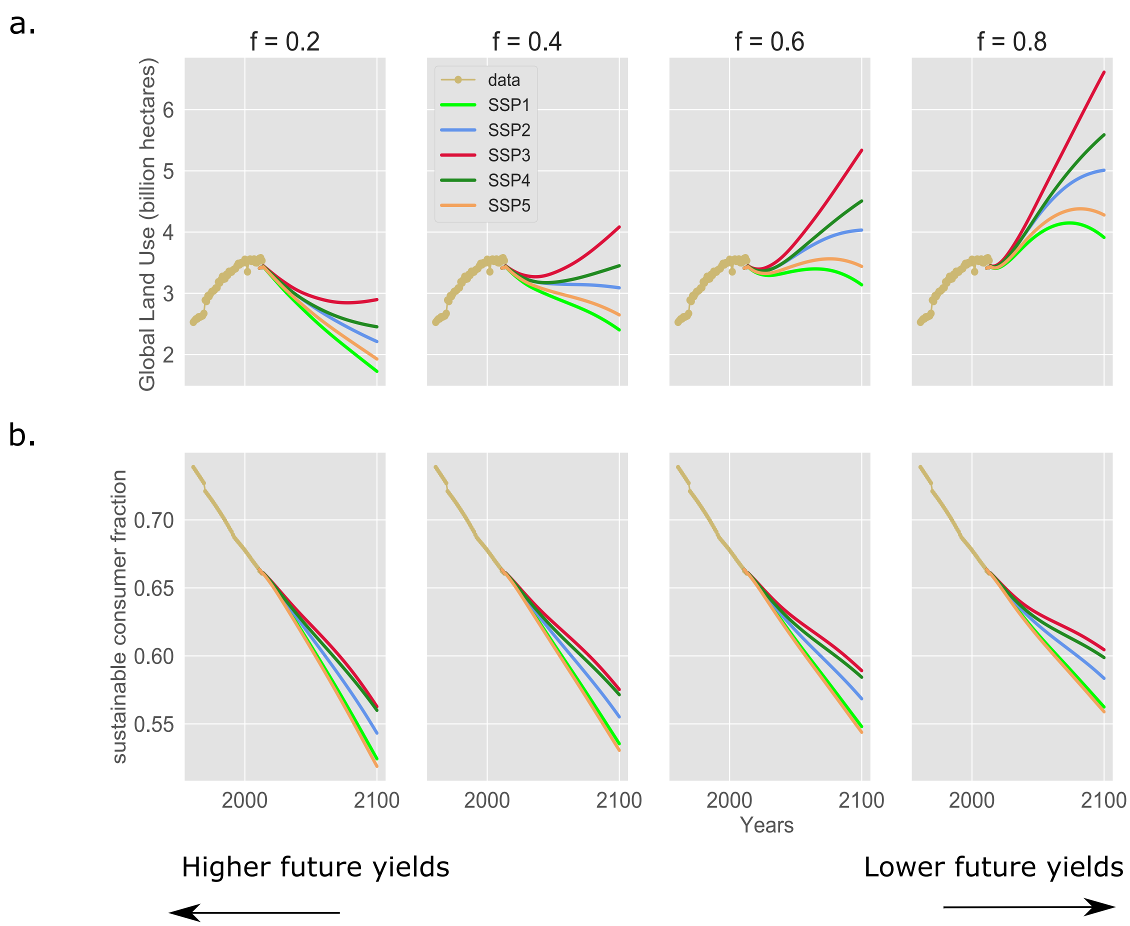

Figure 2.1: **Global land use projections till 2100 under multiple yield and SSP scenarios a.** Global agricultural land use projections till 2100 (excluding land equivalent of food wastage) under 20 scenario combinations. The four columns cover the yield scenarios of $f = 0.2, 0.4, 0.6$ and 0.8. Yellow dots show the time series data for land use from 1961 to 2013. Data from 1961 to 2013 is generated using the model in Rizvi et al. Projections in solid lines begin from 2011 and continue till 2100. **b.** Model projections of fraction of global population consuming sustainably. See Methods for model definition of sustainable consumption. Yellow dots show time series data for fraction of people consuming sustainably between 1961 and 2013. It was calculated as per model definition using data generated by the model in Rizvi et al.

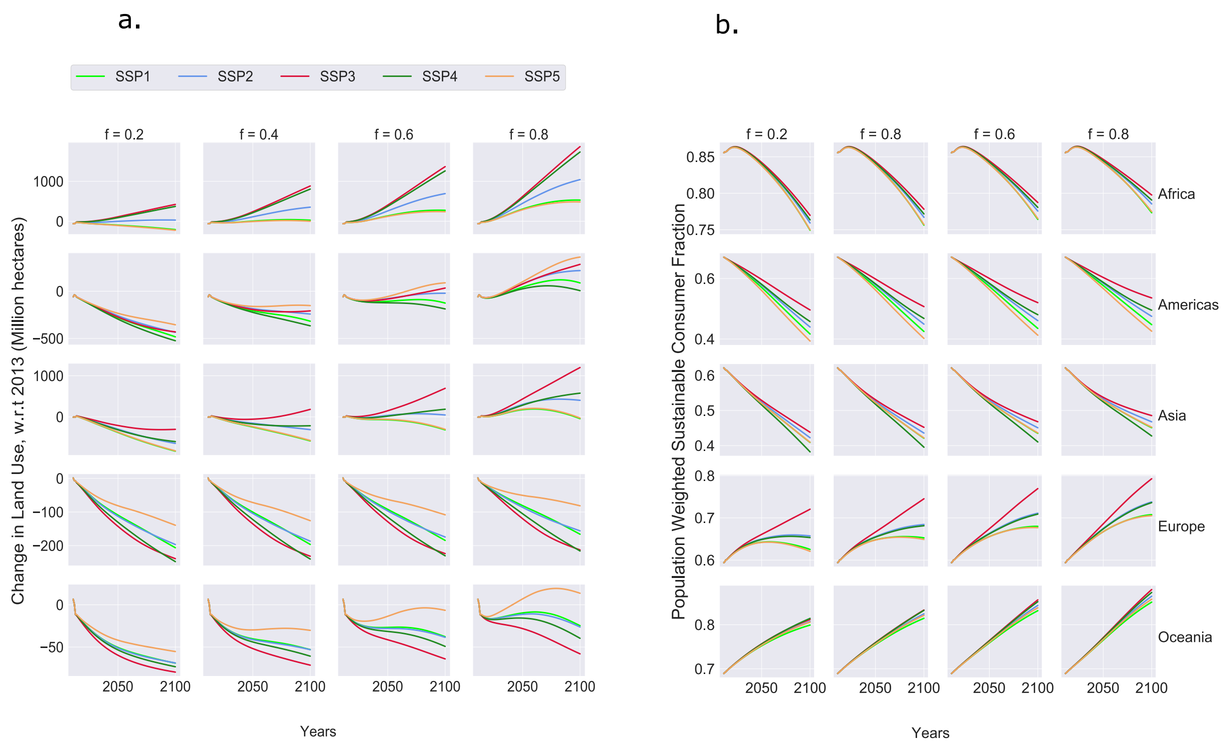

Figure 2.2: **Global land use projections till 2100, broken down continent-wise, reveal heterogeneity under sustainable behaviour in baseline conditions. a.** Projections of change in agricultural land use with respect to 2013 (excluding land equivalent of food wastage) broken down continent-wise into five major regions - Africa, Asia, Americas, Europe and Oceania (see Supplementary Section 5.2 for division methodology). Projections are shown for 20 scenario combinations (combinations of 5 SSP scenarios and 4 f scenarios). **b.** Model projections for fraction of regional population consuming sustainably for 20 scenario combinations. See Methods and Supplementary for formal definitions of sustainable consumption. Only Europe and Oceania show a rise in sustainable consumer fraction over the projecting period (2011 - 2100).

but well-educated population. See Supplementary Figure B.11 for population and income projections under the five SSP scenarios until 2100. For each of the five SSP scenarios, we also explored four scenarios for future agricultural yield: $f = 0.2, 0.4, 0.6, 0.8$, producing a total of 20 scenarios.

2.4.1 Dynamic social-land feedbacks can partially counteract policy

At the global level, the model shows how social dynamics partially counteract land use impacts caused by other trends such as changing per capita income and population size. The model predicts a net decrease in the proportion of individuals practicing a sustainable diet (x, or, 'sustainable consumers' hereafter) from 2013 to 2100 in all scenarios, on account of a high average barrier to adopting a sustainable diet (σ_i) and increasing per capita incomes (Figure 2.1b, and see Supplementary Figure B.6 for global distribution of baseline σ values). A more rapid decline occurs under SSP5 and SSP1, on account of lower population sizes and thus lower land use in those scenarios creating a reduced perception of need to switch to a sustainable diet (Figure 2.1a). There are more sustainable consumers higher under SSP3, on account of higher land use in that scenario. In SSP3, due to reduced global income, unsustainable practitioners cannot consume as much as they could have with a higher income. However, this does not help reduce global land use because population size grows fastest under this scenario. Unsustainable practitioners therefore switch to sustainable diets faster because growing global land use exceeds the barrier to adopting a sustainable diet. Their behavioural change is, however, of little avail. Since their unsustainable consumption is not substantially higher than the sustainable level (due to reduced income in SSP3), the effects of this behavioural change are outweighed by high population growth. On the contrary, in SSP1 and SSP5, higher incomes allow higher consumption for the unsustainable practitioners. But low population growth prevents higher per capita consumption from causing a large rise in global land use. As a result, the temporal evolution to sustainable diets is slower in these scenarios.

Under scenarios of higher future yield ($f = 0.2$ and $f = 0.4$), global land use declines from its 2013 values across most SSPs. The only exception is SSP3 where land use starts to increase again after a period of decline. This occurs because the global population continues growing throughout the 21^{st} century under SSP3. Eventually, the effect of population size outweighs the effect of saturating gains in yield. Under scenarios of lower future yield ($f = 0.6$, 0.8), future land use deviates significantly across the SSPs but generally tends upward. We project land use to go as high as 6 billion hectares in the most extreme scenario ($f = 0.8$, SSP3). SSP scenarios with large initial population growth rate (SSP3 and SSP4) do not reach peak land use by 2100. On account of rapidly expanding land use, the sustainable consumers decline less rapidly than in the higher future yield scenarios, but the overall trend is still downward.

Taken together, these results show how changes in parameters such as population size and per capita in come can cause a social response that partially counteracts those changes.

For instance, SSP5, despite being the most sustainable scenario in other respects, does not exhibit the strongest transition to sustainable diets because the reduced population size in that scenario causes a reduction in land use required, and thus reduces the perceived need to transition to a sustainable diet. Similarly, higher agricultural yields reduce land pressure, and thereby also reduce the perceived need to transition to a sustainable diet. Scenario combinations involving higher future yield and/or SSPs with lower population size cause sustainable consumers to decline, which means that land use ends up being higher than it would be without this feedback between land use and dietary choices.

2.4.2 Continental and country-level land use projections

Projections broken down by geopolitical region reveal significant heterogeneity behind the global trends (Figure 2.2). Europe and Oceania exhibit an increase in sustainable consumers and a decrease in land use across all SSPs. This is because countries in Europe and Oceania have lower inferred barriers to adopting a sustainable diet (σ_i) compared to the rest of the world (Supplementary Figure B.6). With respect to evolution of global land use, they always remain in the regime where sustainability is the dominant behaviour with higher utility. The relative ordering of land use by SSP we saw in the global projections remains consistent at the continent level. These projections also show that an increase in sustainable consumers will not necessarily lead to a decrease in land use, even if that is the general trend. For example, in certain scenarios, Africa, Asia and the Americas show a decrease in land use (with respect to 2013) while the fraction of sustainable consumers also declines, on account of growth in agricultural yield outweighing the effects of income and population growth. For these regions, projections under the SSP3 scenario shows the highest use of land. This is because, for them, population projection under SSP3 is the highest among all SSP scenarios (unlike Europe and Oceania where it is the lowest). That, coupled with a steady decline in sustainable consumers in their population, results in the fastest change in land use. For these regions, the average socio-economic barrier to adopting a sustainable diet is always higher compared to the evolution of global land use in all of the 20 scenario combinations. This indicates that future yield, income and population do not drive the growth of sustainable consumers and the decline of land use identically. The feedback loop between land use and dietary behaviours in our country-level model gets scaled up to the regional level, too. In other words, each region shows a unique behavioural response to change in global land use because of its unique social setting.

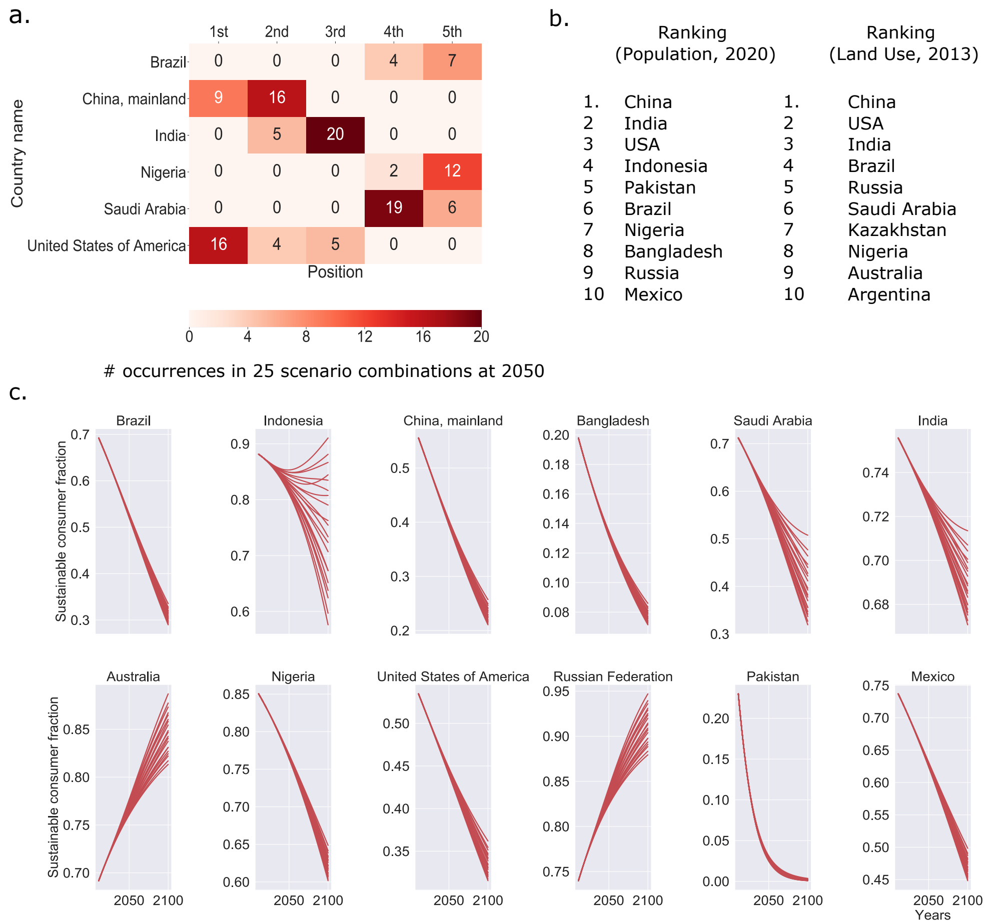

Figure 2.3: **Countries with high population and high land use show general trend of reducing sustainable behaviour under baseline parameters. a.** Ranking of countries based on their total land use across 25 scenarios at 2050. Six countries land at least once inside the top 5 positions in 25 scenario combinations (combinations of 5 SSP scenarios and five yield scenarios: $f = 0.2, 0.4, 0.6, 0.8$ and 1). The heat map indicates the number of appearance of a country at a particular ranking position. China and the USA dominate the first two spots while India, Saudi Arabia and Nigeria dominate third, fourth and fifth positions respectively. **b.** Table showing ranking of countries based on their population (2020, data) and land use (2013, data generated from model in Rizvi et al.). **c.** Model outputs of sustainable consumer fraction for the twelve countries that occupy spots in either of the rankings in b. Ten out of twelve countries show a decrease in sustainable practice. All countries except Australia, Russia and Indonesia (in some scenarios) show decrease in the fraction of people consuming sustainably over all scenario combinations.

Some countries with relatively small population sizes are projected to emerge as front runners of global land use (Figure 2.3). The correlation between population and land use is not absolute, however (Figure 2.3b). In 2013, the countries that had a comparatively lower population but high land use were Kazakhstan (population, 18 million), Saudi Arabia (33 million), Australia (25 million) and Argentina (45 million). Ranking projection of land use show that it is likely the fourth spot, currently occupied by Russia, will be taken over by Saudi Arabia by 2050 (which, in 2013, occupied the fifth spot in land use) (Figure 2.3a). In 2013, the two countries consumed comparable areas of global agricultural land for their respective demands (123 million hectares for Russia and 105 million hectares for Saudi Arabia). The primary reason for Saudi Arabia overtaking Russia can be identified from Figure 2.3c. Over the projecting period, Russia sees an increase in sustainable consumption while a decrease in sustainable consumption is seen for Saudi Arabia. In all the scenarios, their baseline parameter value of σ (barrier to adopting a sustainable diet) places them on opposite regimes of behavior with respect to evolution of global land use. For Russia, sustainability is always the dominant behavior whereas for Saudi Arabia, unsustainable consumption is the dominant behaviour. The switch between positions of Nigeria and Russia can also be explained similarly.

2.4.3 Synergies between socio-land feedbacks and socio-economic factors reduce peak global land use

We found that socio-economic factors as represented in our model–the social learning rate (κ), the barriers to adopting a sustainable diet (σ), and income elasticity (h)–have very large impacts on peak global land use, often ranging in the giga-hectares (Figure 2.4). This is particularly true when higher incomes, higher population sizes and lower future yields force individuals to make a choice between sustainable and unsustainable diets in the face of rapidly expanding global land use. In contrast, when land use does not expand as rapidly due to lower population sizes or higher yields, the perceived need to switch to a sustainable diet is less.

When future yields are lower ($f = 0.8$), the peak global land use is much more sensitive to social processes than when future yield is higher ($f = 0.2$) (Figure 2.4). Low yield means rapidly expanding land use, which in turn stimulates a social response in favour of wider adoption of a sustainable 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 growth also becomes a determining factor in assessing the effectiveness of varying social parameters (Figure 2.4d). In contrast, when future yield is high, land use is lower even though more individuals are practicing an unsustainable diet, and thus changes to parameters governing pace and desirability of a sustainable diet have less impact.

In scenarios where future yields are lower, an increase in the social learning rate (κ) leads to high peak global land use due to faster conversion to unsustainable consumption as per capita income rises (Figure 2.4a). Globally, the barrier to adopting a sustainable diet is too high for sustainability to spread in populations even when global land use increases quickly. In the model, if a sustainable consumer samples their population very often (high social learning rate, κ), they are easily tempted to shift to unsustainable consumption because they see an increased expected utility in switching. The only way to reduce this effect is to reduce the barrier to adopting a sustainable diet (lowering σ, Figure 2.4b). This could be possible by incentivizing consumption of plant protein or reducing the market price of animal protein substitutes. Incentivizing sustainable consumption could also be possible by indirect means, such as increasing public knowledge about health and environmental implications of a high meat diet. Once the barrier to adopting a sustainable diet is sufficiently low, social learning rates would assist in lowering the peak global land use (Figure 2.4b). When σ is lowered, sustainable consumption becomes the dominant behaviour due to its higher utility. In this case, a considerable amount of land is saved even in scenarios where global population growth rate is high (SSP3) and future yields are inferior ($f = 0.8$).

If global land use evolves very slowly due to slow population growth (SSP1, SSP5) and high global yield ($f = 0.2$), the model predicts that sustainable consumption never becomes the dominant behaviour at the global level. This is because L always remains significantly lower to the baseline values of σ in these scenarios. Even with sizeable changes in social parameters, κ and σ, only an insignificant increase in sustainable consumers is achieved. As a result, there is no direct impact on peak global land use. As global land use change is small in these scenarios (and sometimes negative, see Figure 2.1a), there is not enough incentive for individuals to even pay a lowered cost to being sustainable. In such a setting, the key to reducing global land use lies in the consumption patterns of highly prevalent unsustainable consumers. Since global average income is high in these scenarios, an increase in income elasticity can potentially cause negative impacts on global agricultural land use (Figure 2.4a, 2.4c).

However, in the least optimistic scenarios (high population growth rate and low future yields), certain variations of social parameters from their baseline values can alter peak global land use by approximately two billion hectares (twice the size of China). Depending upon socio-economic and yield growth scenarios, the optimal strategy for lowering peak land use changes. Although it is always beneficial to reduce the barrier to adopting a sustainable diet, there can be scenarios where better gains are achieved by modulating the consumption patterns of unsustainable consumers. Varying all three social parameters guarantees a synergy in terms of lowering of peak land use in the 21^{st} century, irrespective of socio-economic scenario. Pragmatically, this is the best strategy since estimating course of current socio-economic and yield scenario can be a difficult task. For example, if population growth rate and global yield are low (SSP1, f = 0.8), reducing income elasticity has no significant effect on global land use (Figure 2.4c). In that scenario, lowering the barrier to adopting a sustainable diet creates the largest impact (a reduction of about 1 billion hectare, Figure 2.4e). The most effective strategy to reduce peak global land use is, hence, to reduce socio-economic barriers of sustainability adoption and income elasticity of consumption simultaneously. Increasing social learning rate also assists in the lowering of land use, provided barriers to adopting sustainable consumption are also reduced.

As seen earlier, the average barriers (σ) of Europe and Oceania are already sufficiently low at the baseline level. They promote an increase in sustainability under the entire spectrum of scenarios (Figure 2.2b). On the other hand, at the baseline level, Africa, Asia and the Americas show an opposite trend. Selective reduction of barriers in these three regions can also significantly impact in reducing peak global land use.

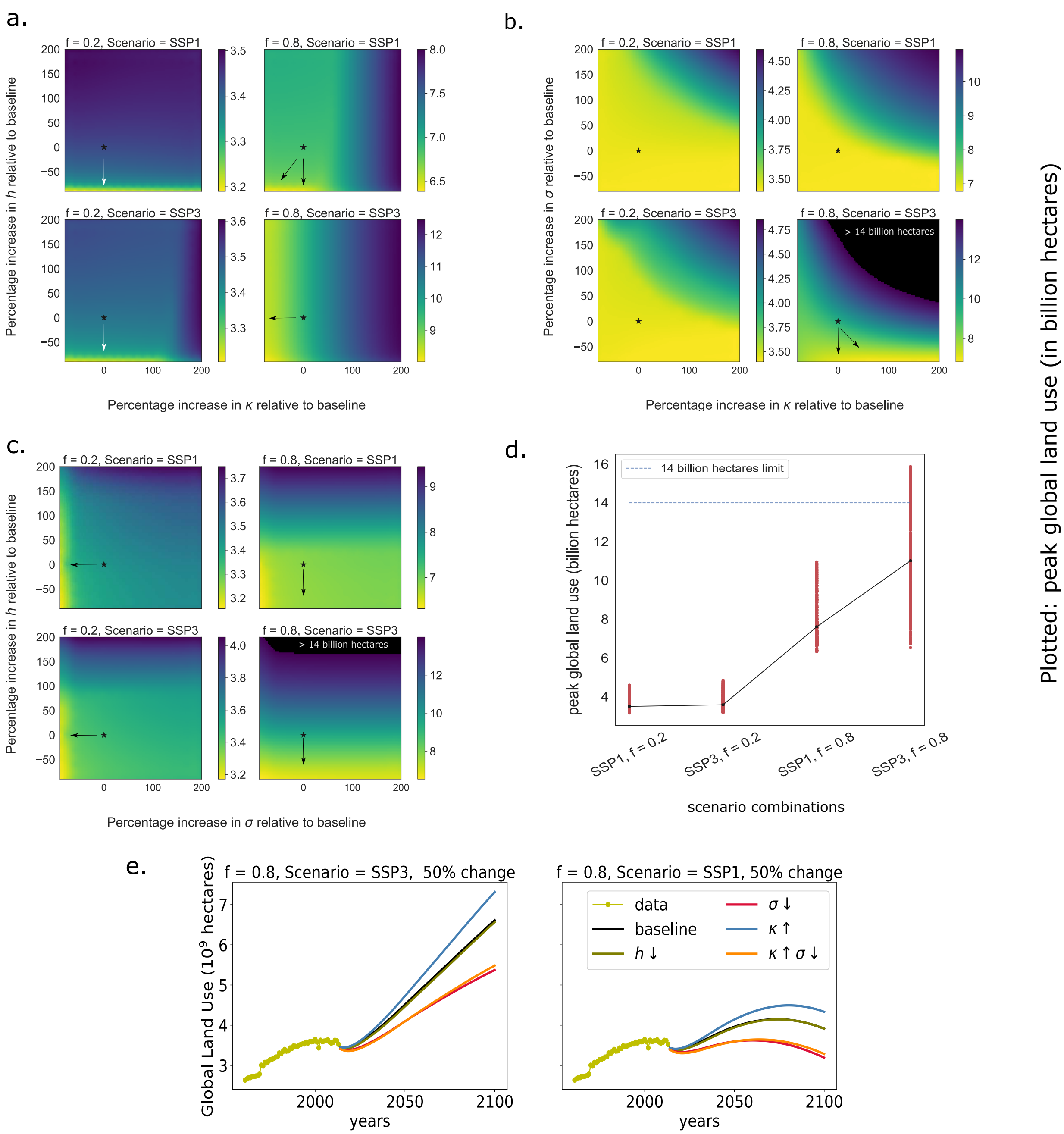

Figure 2.4: (Continued on the following page.)

Figure 2.4: **Variations in social parameters from baseline level impact global land use.** Model output of peak global land use at four scenario combinations - $f = 0.2$, SSP1, $f = 0.2$, SSP3, $f = 0.8$, SSP1 and $f = 0.8$, SSP3. Model projections are evaluated at parameters deviated from their baseline settings. The black star in each plot indicates the position of the baseline parameter in the heat map. **a.** Heat map for peak land use projection with deviations in κ (social learning rate) and h (income elasticity of food consumption) while the value of σ (barrier to adopting a sustainable diet) remains constant at the baseline level **b.** Heat map for peak land use projection with deviations in κ and σ while h remains constant **c.** Heat map for peak land use projection with deviations in σ and h while κ remains constant. All deviations are made within -100% to 200% of the baseline settings. Unit for the color bar in the heat-map is billion hectares. **d.** Peak global land use values from parameter planes in a., b. and c. are plotted versus the scenarios. Average peak global land use increases with increase in f scenario. **e.** Model time series of global land use in the 21^{st} century in scenarios of low global yield. All changes in parameters are made by 50% of baseline value. Reduction in σ saves land the fastest. At low yield scenarios, lowering h has no effect. Increase in global κ with no accompanied decrease in global σ results in substantially higher global land use (w.r.t baseline).

2.5 Discussion

Individual diets are influenced by complex social factors such as religion, concern for health, urbanization, female participation in labour, food prices, and sustainability practices [61, 109, 72, 56]. Several of these factors imply a two-way feedback between land use and dietary decisions. Here we focused on the effect of ballooning global land use as a stimulus for individuals to adopt more sustainable diets, against a backdrop where rising incomes also permits individuals to opt for unsustainable diets instead by eating more land-intensive foods such as meat. We subsumed other factors in decision-making into our phenomenological parameters at the social (κ, σ) and individual (h) level that we inferred from data. We showed how coupled socio-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 future land use under various scenarios for socio-economic development pathways and future agricultural yield. We found that reducing barriers to adopting sustainable diets is an important way to reduce peak global land use. Increasing social learning rates holds the potential to accentuate the mitigating effect of reducing socio-economic barriers (a simultaneous effect shows a reduction of 2 billion hectares in peak global land use). Increasing social learning can result in negative effects if no improvements in lowering barriers are made, however. In some scenarios where sustainability is difficult to achieve due to slow growth of global land use (high yield and low population growth scenarios), reducing income elasticity, globally, can have a significant mitigating effect (on the order of 100 million hectares).

Our minimal model, while serving to illustrate the vital role played by social processes, also made simplifying assumptions that could impact its land use projections. Since we assume a binary one dimensional classification of consumption behaviour: sustainable or unsustainable, it is possible that our model overestimates or underestimates projections for the number of sustainable consumers in a population in order to achieve good fits to the data. Furthermore, over or underestimation is also possible since our model does not take into account the fact that dietary patterns vary based on gender and age. These, however, do not affect the general population trends predicted by our model. Despite being a country with a large proportion of vegetarians, India has shown an increase in consumption of meat (mostly poultry) in its recent history [62, 32]. This trend is captured by our model as well (See Figure 3 of Supplementary Information). A future extension of our model could include a continuous behavioural spectrum along with age and gender structure in the population for more accurate predictions. Future work could also explore the effects of social norms in order to determine how social inertia can accelerate or decelerate behavioural changes, as well as social learning between countries. For the purpose of simplicity in working with country level data, we also assumed homogeneous behaviour within each country by assigning unique parameter values to every country, and this could be relaxed in future research.

A meat intensive diet is not just land intensive (70 % of global agricultural land is used for livestock production). Livestock rearing directly contributes to global warming by being responsible for 14.5 % of anthropogenic greenhouse gas emission such as methane and nitrous oxide [38]. Additionally, recent studies have found that the international livestock supply chain emits 65 TgNyr^{-1}, which is a third of current anthropogenic nitrogen emission [100]. An advanced version of our social process model would take into account the perceived risk of climate change in modeling the behavioural drivers of a population. An additional driver, in that case, could be the peak global temperature anomaly [16].

Future research in coupled socio-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.

2.6 Methods

2.6.1 Coupled Socio-Land Use Model

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

$$c_i^U(t) = (c_i^{U,max}(t) - c_i^S(t))(1 - e^{-h_i(m_i(t)-m_i^0(t))}) + c_i^S(t) \tag{2.1}$$

Where $c_i^{U,max}(t)$ is upper limit of consumption by the unsustainable practitioners, $m_i(t)$ is the average income of the population and $m_i^0(t)$ is the minimum income that can afford the sustainable diet at i in t. The parameter h denotes the elasticity in the behaviour of unsustainable practitioners. If h is large, c^U grows towards $c^{U,max}$ faster with income as compared to when h is small. Note that when average income $m_i(t)$ equals $m_i^0(t)$, the entire population consumes sustainably; that is, they consume $c_i^S(t)$ hectares per capita. The per capita consumption of practitioners of unsustainable diet, c_i^U, approaches $c^{U,max}$ asymptotically as the difference between m_i and m_i^0 gets higher. Our assumption that meat and dairy consumption increases with income has been explored and identified in earlier papers like [12, 61].

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

$$c_i(t) = x_i(t)c_i^S(t) + (1 - x_i(t))c_i^U(t) \tag{2.2}$$

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

$$L^G(t) = \sum_i P_i(t)c_i(t) \tag{2.3}$$

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

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

Hence, as the impact function $L^G(t)$ rises over time due to growing incomes, there is a growing incentive for individuals to switch to a sustainable diet, according to a proportionality constant α_i. The rate of switching becomes faster as the difference between $\alpha_i L^G - \sigma_{0,i}$ grows and vice versa. However, this behaviour to switch to sustainable practice is only effective when $\alpha_i L^G$ is greater than $\sigma_{0,i}$. When $\alpha_i L^G$ is less than this threshold, $\sigma_{0,i}$, the proportion of unsustainable practitioners grows, the rate being determined by the absolute difference between $\alpha_i L^G - \sigma_{0,i}$. We call the parameter $\sigma_{0,i}$, the socio-economic barrier to adopting a sustainable diet in i. Assuming a social learning rate of $\kappa_{0,i}$ for i we can write the evolution of sustainable practitioners as follows:

$$\frac{dx_i}{dt} = \kappa_{0,i} x_i (1 - x_i) \Delta e, \quad x_i(t_0) = x_{0,i} \tag{2.4}$$

After some rescaling of parameters we obtain:

$$\frac{dx_i}{dt} = \kappa_i x_i (1 - x_i)(L^G(t) - \sigma_i), \quad x_i(t_0) = x_{0,i} \tag{2.5}$$

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

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

The upper bound of per capita consumption, $c^{U,max}$, is calculated by assuming that the maximum diet is the one that allows highest intake of items that belong in the meats and dairy diet groups. Similarly, for c^S, we assume that sustainable diet is the one that allows least consumption of items in those groups. Our assumption is backed by numerous studies that have found meat intensive diets to be environmentally unfriendly and land-intensive [74, 85]

$c^{U,max}$ and c^S can be calculated between 1961 and 2013 for countries whose data is reported in FAOSTAT's food balance sheets [32]. 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 diet by replacing its average consumption of items in the 'meats' and 'dairy' groups (in kcals/capita/day) with the consumption values of the countries that consumed the most of those items that year. Similarly, for the minimum sustainable 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, oils), remain the same as reported data. An example of such a construction is shown in Appendix Table A.1). The method of evaluating these bounds are explained with more detail in Appendix Section A.1.1.

Once these hypothetical maximum and sustainable diets are constructed for a country i, we use the model developed in Rizvi et al. [78] to calculate the total land required to generate that per capita dietary demand for the population of i in t (see Appendix Section A.2 or Introduction Section 1.5.1 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 diet, c^S if sustainable diet).

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).

2.6.3 Definition of land use: Data and Methods

We use the model developed in [78] to generate the country-level time series data of average per capita land use between 1961 and 2013. The model is described briefly in Appendix Section A.2. The UN FAOSTAT 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 model in [78] accounts for differential yields of food sources, the data for per capita land use, as generated by model in [78], 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 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 land that is required to generate the food that ends up being consumed by humans. Land equivalent of food wastage is not considered in our calculations. The data reported by UN FAOSTAT's land statistics division [33] accounts for land used for all agricultural purposes. This includes land equivalent of food wastage. In Supplementary Figure B.1, we see the quantitative difference between their time-series and our global model output. FAOSTAT estimated that 1.4 billion hectares were lost due to food wastage in the year 2007 [29]. This number matches exactly with the difference between the two series at 2007 in Supplementary Figure B.1.

2.6.4 Population, income and f (yield) scenarios:

We borrow the SSP scenarios (Shared Socioeconomic Pathways) introduced in [77] 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 [26] for obtaining future projected values of country level population and income. In Appendix Section A.4 we list down the countries that are included in our analysis. We also provide reasons for the exclusion of certain countries. The choice for OECD Env-Growth was made because it covers projections for maximum number of countries among the existing models.

The bounds for maximum and minimum per-capita consumption ($c^{U,max}$ and c^S) 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 $c^{U,max}$ and c^S 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 $c^{U,max}$ or c^S) 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 c can either be $c^{U,max}$ or c^S for a country i. 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:

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

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 β is adjusted such that continuity is maintained at 2013 between the initial trend, ae^{bx}, and the projected trend $c(t)$. That is,

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

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

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

2.6.5 Parameter plane analysis

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

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

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

Chapter 3

Conclusions and Future Work

In Section 2.5 I discussed some of the conclusions and limitations of the results and the model presented in Chapter 2. In this chapter, I discuss a few more conclusions and limitations while charting the pathway for future research in coupled human-land system models.

3.1 Conclusions

The concept of incentivizing sustainable consumption for boosting dietary change is not entirely new. Quite recently in [70], authors conclude that the fastest mitigating pathway of reducing food's environmental impact is through changes in dietary behaviour. Their findings show that producers have limits on how far they can reduce impacts from their end. In this thesis, we show the quantitative impact of such incentivization through a mathematical framework. Additionally, we also explore other potential endogenous system parameters that can heavily accelerate the mitigation of such incentivization. The social learning rate is one such parameter. However, without incentivization it can have negative impacts. Under the current social learning rate, there is little hope in containing massive demands of land intensive items if incentivization of sustainable diets are not implemented soon.

Sustainability is a complex issue, especially at the individual level. It might seem hopeless to adopt a sustainable diet when the outcomes of such behaviours are almost never physically observable. There is no direct way for consumers to know how much land they are using up for their consumption due to complicated supply chains of food items and limited public knowledge of agricultural systems. To address this problem, several policy-advising researchers suggest a mitigation framework where producers monitor their own impacts by choosing from a range of available practices and simultaneously communicate their impacts to consumers through their products [70]. Observable efforts from the producer side in mitigating land and environment impacts can directly incentivize consumers to reduce their consumption of heavy impact items. The communication can be implemented through a combination of environment labels or taxes that reflect the environmental cost of a generating a product. The role of researchers in this grand mitigation scheme is to continually provide multiple mitigation options to farms, industry and retailers through studies and observations [70]. Humans can acquire protein substitute of animal products by consuming food that is not grown on land. This allows inclusion of seafood and fishes in diets (which is currently not considered in the model). However, access to seafood can vary depending upon the geographical location of a country. For example, a land-locked country has lesser access to fish protein when compared to a sea-bordering nation (with exceptions). Over-reliability on aquaculture is also not advisable due to environmental impacts of over-fishing on coastal ecosystems [47, 80].

Non animal product food groups are not always sustainable in terms of land consumption. For example, the food group of 'oils' has a very low effective yield compared to the other groups (very similar to bovine and ovine meat, see Figure 1.3). Production of consumable oil has been historically associated with tropical and equatorial deforestation (e.g. palm oil) [104, 17]. Food groups can be legitimately labeled as 'vegetarian' or even 'vegan' though they are involved in unsustainable practice of production. Due to complex supply chains of the food industry, it is difficult from the consumers' perspective to distinguish between a sustainably produced item and an item produced through unsustainable practice.

In vitro agriculture [27] and vat-grown meat [76] are some of the upcoming sustainable alternatives to traditional livestock rearing for meat. These procedures involve developing meat and meat substitutes using cell culture and tissue engineering. Progress in industrializing such alternatives at low cost holds the potential to revolutionize the food industry, and hence global agriculture. Efforts such as the recently popular *plant-based burger* can also be of heavy impact with the correct commercialization.

3.2 Limitations and Future Work

The behavioural side of the coupled human-land system model is simplistic and does not capture some of the deeper complexities of the social processes behind dietary behaviour. Global dietary behaviour is a complex system that is affected by a variety of factors that currently lack a representation in the modeling (as was discussed in Section 2.5). Our phenomenological parameters subsume some of the more complex decision making factors into them. For example, a high behavioural threshold (a high σ) can capture the cultural norm of consuming meat in a population. With a separate representation for other external factors in the model, it could be easier to study their individual effects on global land use.

The model does not distinguish between 'a sustainable consumption due to choice' and 'a sustainable consumption due to force'. Undernourished countries show, by definition, trends of sustainable consumption because of reduced levels of intake in all food-groups. The behavioural threshold barrier (σ_i), in the current version of the model, hence, also accounts for the economical barrier to adopt a reduced diet. A future model must include a compartmentalization of these two qualitatively different behaviours. A simpler extension of this work can address this issue by considering a separate model for countries that have average consumption below a specific nutritional threshold. The modified model should allow scaling of consumption with income for populations until they reach a standard nutritional level.

Dietary behaviour is heterogenous. It can be argued that the modeling approach of assigning homogenous consumption to all the unsustainable practitioners in a population (based on the average income of the population) is reductive since it does not account for heterogenity in consumption levels. However, due to limited availability of data regarding income distribution in countries, this approach was the only way to capture the relationship between income levels and consumption patterns. Furthermore, food prices have been shown to affect dietary consumption patterns too [61]. In an advanced version of the model, the parameter m_0 (currently, the minimum income that can afford a sustainable diet) should also account for animal product prices in the local market of the population.

One of the major drivers of dietary behaviour is concern for health and nutrition [35, 79, 24]. Meat consumption levels in high and medium income countries has reached levels that negatively impact human health [61]. For example, animal protein rich diets have been shown to be highly correlated with obesity [71], cardiovascular diseases [106], strokes and types of cancer [65]. Although these factors are implicitly represented in the social parameters, κ, σ and h, a better understanding of them is possible if they are treated separately in the model. At higher income levels, reduction in consumption may not be triggered only due to concern for climate and the environment. Utility functions for payoffs should include perceived health cost of consuming animal products and perceived health benefits of consuming plant proteins. These payoffs might increase or decrease with more public consciousness about health benefits of food consumption. Currently, this effect is captured by the income elasticity parameter, h. One can expect the this parameter to fall as populations become more aware of the health impact of diets.

For certain countries, the social-land use model performs well in fitting the data but fails in explaining the behavioural dynamics in the population with clarity (e.g. Australia). For Australia, the fitted value of σ (the parameter representing barriers to adopting a sustainable diet) is an unrealistically low value which is significantly lower than the global average value of σ. For Australia this value is 1.03 whereas the global average is 1.17×10^8. Such anomalous results are also seen for countries like Ukraine, France, Israel and Argentina. Since σ is significantly low for these countries, estimates of sustainable consumer proportion increases rapidly for them (as compared to other nations). This, however, does not capture the actual behavioural dynamics within those countries (since it is unrealistic to expect such rapid behavioural change in populations). This primarily happens due to the fact that these countries have made significant progress in utilizing land as compared to other nations in the world (i.e. they have seen a very large drop in their per-capita land use over 1961-2013). Their average per-capita land use over 1961 to 2013 falls too fast to be realistically captured by our socio-land use model. To compensate for that (i.e. to provide the optimal fitting results), the parameter estimating algorithm assigns low values of σ to these countries. Rapid change in per capita land use, due to factors not concerning dietary behaviour, is attributed to increase in sustainable consumption. In other words, it cannot be ascertained whether endogenous behavioural mechanisms assist in lowering consumption in these countries. Effects of other non-dietary factors corrupt the standard interpretation of results for some select countries.

The coupled social-land use model in this thesis only addresses land equivalent of global dietary consumption. Although dietary consumption contributes almost two-thirds of net global agricultural land use (see Figure B.1), several other factors are significantly important as well. Majority of the remaining one-third portion of total land use is contributed by food wastage at the production level. Other purposes like crops for biofuel and non dietary consumption (like oil-crops for making soaps, pet food, tobacco, cotton etc.) contribute to the remaining portion.

There is no absolute definition for a sustainable diet. However, it is well understood that it is a diet that has reduced levels of meat and dairy consumption. In this model, for the purpose of simplicity, I have strictly defined sustainable diets for countries at a given year (see Appendix section A.1.1). Normally, a diet $\mathbf{D}_1$ is considered more sustainable than a diet $\mathbf{D}_2$ when the former requires less land to produce. This definition allows a continuous spectrum for sustainable consumption. In an advanced extension, it could be worthwhile to model sustainable diets in a more relaxed sense. This would assist in better estimating the actual proportion of sustainable consumers in a population by reducing the risk of overestimation (or underestimation).

In this thesis, the notion of sustainable consumption is equated with less usage of land for agricultural purposes. However, for some specific local cases, the opposite might be true. Agricultural land expansion can occur via multiple methods. Although primarily, agricultural land expansion occurs by replacing forests and forest-grassland mosaics [55, 97], there are some examples where barren (desert) land areas were greened for agriculture [82]. Furthermore, farms covering small areas can also be 'unsustainable' due to practice of unsustainable methods of agriculture in them. The model in this thesis does not encompass these wider aspects of sustainability.

It is possible to build increasingly complex conceptual models of dietary behaviour by making several assumptions on mechanistic relationships between supposed drivers and observables. A very complicated model with excellent fits to data can be misleading due of overestimation. This however, does not imply that the philosophy of parsimony (*Occam's* *razor*) is automatically the best either. If model projection is the sole objective of model construction, then, care must be taken to avoid both over and underestimation. This is especially important for a very complex system like spatial dietary behaviour which has innumerable unidentified and interconnected drivers. In this thesis, the presented model serves mostly the purpose of understanding the evolutionary dynamics of sustainability in human consumptional behaviour. Phenomenological parameters are sufficient for a broader understanding of the impact of certain specific drivers. Future modeling approaches along similar lines can help to understand complex systems in a more meaningful way, for the purpose of sustainability.

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APPENDICES

Appendix A

Supplementary Information - Future of Global Land Use and Sustainable Consumption with a Social Learning Model

A.1 Method of parameter estimation

For each country $i \in I$, our land-use model is represented by the following coupled equations:

$$c_i(t) = L_i(t)/P_i(t) = x_i(t)c_i^S(t) + (1 - x_i(t))c^U(t) \tag{A.1}$$

$$c_i^U(t) = (c_i^{U,max}(t) - c_i^S(t))(1 - e^{-h_i(m_i(t)-m_i^0(t))}) + c_i^S(t) \tag{A.2}$$

$$L^G(t) = \sum_i P_i(t)c_i(t) \tag{A.3}$$

$$\frac{dx_i}{dt} = \kappa_i x_i(1 - x_i)(L^G(t) - \sigma_i), \quad x_i(t_0^i) = x_{0,i} \tag{A.4}$$

Note that equations A.3 and A.4 couple together the model equations for all $i \in I$. The goal of the parameter estimation process is to evaluate the parameters κ_i, σ_i, h_i and $x_{0,i}$ for a country i given we have the time series data of i's per-capita land use. We define the time period over which we parameterize our model as $[t_0^i, t_f^i]$. For most countries, $t_0^i = 1961$ and $t_f^i = 2013$. There are some exceptions like the Russian Federation for which $t_0^i = 1992$. The yearly data available to us from [32] is within the range of 1961 to 2013. For the parameter estimation part, we **do not** use equation A.3 to feed the differential equation in equation A.4. Instead, we read $L^G(t)$ from the data. We generate this data from the model in [78]. The model is discussed in detail in section A.2 of this document (also in Introduction Section 1.5.1). This time series is shown in Supplementary Figure B.1 as the yellow time series.

The parameter estimation process for i also requires as input the time series $c_i^{U,max}(t)$, $c_i^S(t)$ and $m_i^0(t)$. These time series should cover all the years over which parameterization is being performed. That is, they should be defined in $[t_0^i, t_f^i]$. In the subsections A.1.1, A.1.2 we discuss methods to obtain these time series. In subsection A.1.3, we discuss a method that reduces the number of free parameters from four to three by evaluating $x_{0,i}$ from h_i and the first data point. In subsection A.1.4, we discuss the optimization technique we use to parameterize our model. In subsection A.1.5, we discuss methods to determine the parameterization period, $[t_0^i, t_f^i]$ for i. In section A.4, we discuss how the set I is constructed for this work. We explain reasons for inclusion and exclusion of countries from the set I.

A.1.1 Method for generating $c_i^{U,max}(t)$ and $c_i^S(t)$ time series

We define $c_i^{U,max}(t)$ and $c_i^S(t)$ to be the theoretical maximum of per capita land use of non practitioners of sustainable diet and the per capita land use of sustainable practitioners in

i at t respectively. Let us represent the Rizvi et al. model as a function, $R(.)$, that maps a diet $\mathbf{D}$, a country i, and a year t into a land use value for the country i at t. It implies that if the population of i at t consumed the per capita diet $\mathbf{D}$ on average, $R(\mathbf{D}, i, t)$ hectares of land would have been spent, globally, to generate the demand. We can then define $c_i^{U,max}(t)$ and $c_i^S(t)$ accordingly:

$$c_i^{U,max}(t) = R(\mathbf{D}^{max,i}(t), i, t)/P_i(t)$$

$$c_i^S(t) = R(\mathbf{D}^{S,i}(t), i, t)/P_i(t)$$

Where $\mathbf{D}^{max,i}(t)$ is a hypothetically large diet that is considered as the theoretical maximum diet for non-practitioners and $\mathbf{D}^{S,i}(t)$ is a sustainable diet consumed by sustainable practitioners in country i at t. $P_i(t)$ is the population of country i at t.

A diet $\mathbf{D}$ is a caloric break down of per capita consumption in 7 food groups - fruits, vegetables, grains, meats, dairy, sugar, oils. Using data from the UN FAOSTAT Food Balance Sheets, we can construct $\mathbf{D}^i(t)$, the average diet for i at t, by adhering to the food group divisions defined in Rizvi et al. We design $\mathbf{D}^{max,i}(t)$ and $\mathbf{D}^{S,i}(t)$ by keeping caloric values under all groups in $\mathbf{D}^i(t)$ same except the caloric values under meats and dairy groups. For $\mathbf{D}^{max,i}(t)$ we replace the meats and dairy caloric values in $D^i(t)$ with the cumulative dietary consumption of countries in I that consumed the most in that year in items that belong to the groups of meats and dairy. A similar approach was taken while designing $\mathbf{D}^{S,i}(t)$. Per capita meats and dairy caloric intake in $D^i(t)$ was replaced by the cumulative dietary consumption of countries in I that consumed the least in that year in items that belong to the groups of meats and dairy. We take an example to explain this better. For this example we take i to be the United States of America and t to be 2010. From UN FAOSTAT Food Balance Sheet data, the construction of $D^{USA}(2010)$ looks as follows (all units in kcals/capita/day):

$\mathbf{D}^{USA}(2010) = \{$ fruits: 122, vegetables: 163, grains: 61, meats: 621, dairy: 441, oils: 671, sugar: 591$\}$

The meats and dairy groups, as defined by Rizvi et al. [78], contain the food balance sheet items bovine meat, goat and sheep meat, pig meat, poultry meat, eggs, milk and butter (ghee). The items bovine meat, goat and sheep meat, pig meat, poultry meat and eggs belong in the meats group and the items milk and butter(ghee) belong in the dairy group. Table A.1 notes from data the highest and lowest consumers of these seven items in the year 2010 along with their respective average per capita calorie intake. We do not consider countries for which the consumption is zero while evaluating the lowest

Item	Food Group	Highest (kcals/capita/day)	Lowest (kcals/capita/day)
Bovine Meat	Meats	Argentina (342)	Liberia (2)
Sheep and Goat Meat	Meats	Mongolia (327)	Congo (1)
Pig Meat	Meats	Hong Kong (385)	Guinea (1)
Poultry Meat	Meats	St. Lucia (273)	Chad (2)
Eggs	Meats	Japan (76)	Cameroon (1)
Milk	Dairy	Iceland (562)	Liberia (5)
Butter (Ghee)	Dairy	New Zealand (187)	Angola (1)

Table A.1: Highest and lowest Meats and Dairy item consuming nations in 2010 and their respective average per capita caloric consumption from UN FAOSTAT Food Balance Sheet [32]

consuming countries for a concerned item. If the group values in Table A.1 are added up then, the diets $\mathbf{D}^{max,USA}(2010)$ and $\mathbf{D}^{S,USA}(2010)$ would be as follows:

$\mathbf{D}^{max,USA}(2010)$ = { fruits: 122, vegetables: 163, grains: 61, meats: 1403, dairy: 749, oils: 671, sugar: 591}

$\mathbf{D}^{S,USA}(2010)$ = { fruits: 122, vegetables: 163, grains: 61, meats: 7, dairy: 6, oils: 671, sugar: 591}

Once constructed, these maximum and sustainable diets are fed into the Rizvi et al. land use evaluation model. It tells us how much land would have been spent globally if United States of America consumed these hypothetical per capita diets in 2010. We divide the land values obtained from the model with the population of USA in 2010 to receive the values of $c_{USA}^{U,max}(2010)$ and $c_{USA}^{S}(2010)$. Supplementary Figure B.2 shows the constructed time series $c_i^{U,max}(t)$, $c_i^S(t)$ and $c_i(t)$ for USA, China, India, Russia, Brazil and Australia for every year between 1961 and 2013. Time series for Russian Federation is shown only from 1992 to 2013 since it did not exist per se prior to 1992.

A.1.2 Data Source for $m_i(t)$ and Method for generating $m_i^0(t)$ time series

In our model, $m_i(t)$ is defined as the average income of the population of country i at year t. We collect the per capita income data from the World Bank database [6]. We use the data listed under GDP per capita, PPP for our purpose.

In our model, $m_i^0(t)$ is defined as the minimum income required to afford the sustainable diet $\mathbf{D}^{S,i}(t)$ in i at t. We set it to the minimum wage (and for some cases the living wage) in i at t. We obtain the minimum wage data for the OECD countries from the Real Minimum Wage data-set compiled by the Organisation for Economic Co-operation and Development (OECD) [91]. If no minimum wage data is obtained from the first source, we set $m_i^0(t)$ to the living wage of i at t. Living wage data is obtained from the source: [45]. If a particular country is not covered by either of the aforementioned sources, we rely on the sources compiled in the online, community maintained, article [108]. For some countries, none of the above sources provide any minimum or living wage data. These cases are specially handled and are discussed in more detail in subsection A.1.4.

Since our sources of minimum wage (or living wages) data do not report these wages for all the years we wish to parameterize our model over, we evaluate $m_i^0(t)$ for all years between t_0^i to t_f^i using the following back-extrapolating method:

$$m_i^0(t) = m_i(t) \cdot (m_i^0(t_r^i)/m_i(t_r^i)) \quad t \in [t_0^i, t_f^i]$$

Where t_r^i is the year at which minimum wage statistic was reported. Here we assume that minimum/living wage of countries maintain a constant ratio with the respective country's average income over all years in $[t_0^i, t_f^i]$. Since we have average income data for all the years in $[t_0^i, t_f^i]$, we can use the above method to back extrapolate the values of $m_i^0(t)$ for all years that lie in the period, $[t_0^i, t_f^i]$.

A.1.3 To determine $x_{0,i}$ from h_i and data

At the onset, there are four parameters unknown for the parameter estimation problem - κ_i, σ_i, h_i and $x_{0,i}$. In order to reduce the dimensionality of the parameter search space, we discuss a method to evaluate $x_{0,i}$ from the first data point and h_i. This operation reduces the number of free parameters from 4 to 3 and assures that the c_i predicted from the model at the first time point t_0^i is equal to the first data point at t_0^i.

For a h_i, we can write the following at t_0^i:

$$L_i(t_0^i)/P_i(t_0^i) = x_i(t_0^i)c_i^S(t_0^i) + (1 - x_i(t_0^i))c_i^U(t_0^i)$$

In this equation $x_i(t_0^i)$ is the initialization, $x_{0,i}$, of the differential equation for x_i. $L_i(t_0^i)$ and $P_i(t_0^i)$ are taken from data. This implies that:

$$x_{0,i} = x_i(t_0^i) = \frac{c_i^U(t_0^i) - (L_i(t_0^i)/P_i(t_0^i))}{c_i^U(t_0^i) - c_i^S(t_0^i)} \tag{A.5}$$

Where,

$$c_i^U(t_0^i = (c_i^{U,max}(t_0^i) - c_i^S(t_0^i))(1 - e^{-h(m_i(t_0^i)-m_i^0(t_0^i))}) + c_i^S(t_0^i)$$

Hence, given a value of h_i, it is possible to derive $x_{0,i}$ from equation A.5 provided there is knowledge about the following data at time t_0^i: $L_i(t_0^i)$, $P_i(t_0^i)$, $c_i^{U,max}(t_0^i)$, $c_i^S(t_0^i)$ and $m_i^0(t_0^i)$. This operation reduces the search space for the parameters from 4 to 3 as $x_{0,i}$ can be determined from h_i and data implicitly.

For ease of expression in the next subsection, let us define a mapping $\xi(.)$ that relates this implicit relationship between h_i and $x_{0,i}$. The function $\xi(.)$ maps the tuple (h_i, i, t_0^i) to a value of $x_{0,i}$ such that equation A.5 is respected. That is,

$$x_{0,i} = \xi(h_i, i, t)$$

It is worth noting that equation A.5 also puts bounds on the search space of h_i since $x_{0,i}$, by definition, always lies between 0 and 1. Bounds on h_i makes further reduction in the parameter search space.

A.1.4 Algorithm for Parameter Estimation

Note from equation A.1 that $c_i(t)$ is also function of the parameters κ_i, σ_i, h_i and $x_{0,i}$. We use the following alternate represenions of $c_i(t)$:

$$c_i(t) \equiv c_i(t, \kappa_i, \sigma_i, h_i, x_{0,i}) \equiv c_i(t, \kappa_i, \sigma_i, h_i, \xi(h_i, i, t)) \equiv c_i(t, \kappa_i, \sigma_i, h_i)$$

Given the time series of per-capita land use of a country i in $[t_0^i, t_f^i]$ as input data, the task is to find the optimal parameters κ_i, σ_i and h_i so that the loss function defined between the data and the model is minimized.

The loss function that we choose to determine the deviation of the model output from the data is a weighted root mean square metric where the weights are linearly increasing from t_0^i to t_f^i. Imagine N^i time series data points $\{d_1, d_2, ..., d_{N^i}\}$ and a corresponding model output time series $\{m_1(\theta), m_2(\theta), .., m_{N^i}(\theta)\}$. We define our weighted loss function $L(\theta)$ between data and model output as follows:

$$L(\theta) = \frac{1}{N^i \sum_{k=1}^{k=N^i} w_k} \sum_{k=1}^{k=N^i} w_k (d_k - m_k(\theta))^2, \quad w_k = k \tag{A.6}$$

Let us represent the time series data that we have of per capita land use for i from t_0^i to t_f^i as: $\{c_i^d(t_0^i), .., c_i^d(t_f^i)\}$. For each country, $i \in I$, we have N^i equi-spaced data points including t_0^i and t_f^i . That is $N^i = t_f^i - t_0^i + 1$. Since we deal with yearly data, t_0^i and t_f^i are the starting and ending years. Our parameter estimation algorithm tries to evaluate the optimal values of κ_i, σ_i and h_i so that the following is minimized:

$$\frac{1}{N^i \sum_{t_j \in [t_0^i, t_f^i]} w_{t_j}} \sum_{t_j \in [t_0^i, t_f^i]} w_{t_j} (c_i^d(t_j) - c_i(t_j, \kappa_i, \sigma_i, h_i))^2, \quad w_{t_j} = t_j - t_0^i \tag{A.7}$$

For parameter estimation, we do not use the closed loop feedback. That is, we do not feed equation A.3 into equation A.4. Instead, we use the time series of total global land use as $L^G(t)$, into equation A.4 (evaluated from data). This time series is the same as the yellow time series seen in Figure B.1 of this text. This time series is evaluated using the model described in [78]. The model is available as Python scripts in: Saptarshi07/Dietary-Trends-Tools.

For countries where the minimum/living wage statistic is absent completely, we optimize for parameters σ_i, h_i and $m_i^0(2018)$ while assuming a value of κ_i. The assumed value of κ is estimated by averaging the κ values of geographically nearby countries. For example, two such countries are Norway and Sweden. We use the evaluated value of κ from Denmark and Finland to fill in the value of κ for Norway and Sweden. Similarly, for Niger, we take the evaluated κ values of Mali, Nigeria and Benin to fill in its κ value.

We use a combinatorial optimization approach in our numerical algorithm to determine the near-optimal parameter values for our model. The three parameters that we estimate can either be κ, σ and h or, they can be σ, h and $m^0(t_r^i = 2018)$ depending on whether minimum wage statistic is available for the country. Let us denote the three parameters we want to estimate with our algorithm as θ_1, θ_2 and θ_3.

At the beginning of our algorithm, we set theoretical bounds for our parameters. The range for parameter θ_i is denoted as $[\theta_{i,l}, \theta_{i,u}]$. Here l and u stand for lower and upper bounds. For example, the theoretical bounds for $log(\kappa)$ was taken to be $[-12, 0]$ and the theoretical bounds for $log(\sigma)$ was taken to be $[0, 12]$. For $log(h)$ it was $[-8, 0]$ and for $m^0(t_r^i)$ it was $[0, m(t_r^i)]$. All logarithms here are with base 10. The search for parameters is conducted in the logarithmic space. The bounds for parameters remain constant for every country throughout the parameter estimation process. Our numerical algorithm for optimization requires two other input hyper-parameters. We call them the depth (D) and runs (R) of the algorithm.

Algorithm:

1. Get R equidistant points inside each bound range, $[\theta_{i,l}, \theta_{i,u}]$. Let these points be - $\{\theta_{i,0}, .., \theta_{i,k}, ...\theta_{i,R-1}\}$. Here $i = 1, 2, 3$. $\theta_{i,l} = \theta_{i,0}$ and $\theta_{i,u} = \theta_{i,R-1}$

2. For all R^3 combination of parameters, find the combination for which $L(\theta)$ is minimum. Let them be $\theta_{1,a}$, $\theta_{2,b}$ and $\theta_{3,c}$.

3. Reset the bound for parameter 1 as follows: $\theta_{1,l} = \theta_{1,a-1}$ and $\theta_{1,u} = \theta_{1,a+1}$. If $a = 0$ then $\theta_{1,l} = \theta_{1,a}$ and if $a = R - 1$ then $\theta_{u,l} = \theta_{1,a}$. Reset bounds for parameters θ_2 and θ_3 similarly.

4. Do step 1-3 for remaining $D - 1$ (depth - 1) number of times.

5. The optimal evaluated parameters are $\theta_{1,a}$, $\theta_{2,b}$ and $\theta_{3,c}$ after D runs.

We use $D = 5$ and $R = 10$ for the parameter estimation process. These hyper parameters were observed to be large enough to saturate error values. We use the loss function defined in Equation A.7 as $L(\theta)$. As mentioned earlier, the search is conducted in the log-space. This means that we obtain the optimal parameters in their logarithmic form - $log(\theta_{1,a}), log(\theta_{2,b})$ and $log(\theta_{3,c})$.

A.1.5 Choice of t_0^i, t_f^i and discussion

As mentioned in the previous subsection A.1.4, all the time series data that we work with are yearly and between 1961 to 2013. So, t_0^i and t_f^i are also years between 1961 and 2013. For every country i a decision needs to be made before parameterization about the choice of t_0^i and t_f^i. The following points note down the steps for this choice:

1. t_0^i and t_f^i are always integer values in $[1961, 2013]$. $t_0^i < t_f^i$ should always be maintained.

2. For no year in $[1961, t_0^i) \cap (t_f^i, 2013]$ per capita land use data for i should be available.

An example of i where t_0^i is not 1961 is the Russian Federation. For Russia, t_0^i is 1992 since the country did not exist by that name prior to 1992 and so no data for per capita land use is available for it between 1961 and 1991. Similarly, an example where t_f^i is not 2013 is the USSR.

A.2 Brief description of land use evaluation model in [78]

We represent the Rizvi et al. model as a function, $R(.)$, that maps a diet $\mathbf{D}$, a country i, and a year t into a land use value. That is, if the population of i in year t consumed the average per capita diet $\mathbf{D}$, $R(\mathbf{D}, i, t)$ hectares of land would have been spent, globally, to generate the demand. For this function t is an integer such that $1961 \leq t \leq 2013$. A diet is defined, mathematically, as a column vector of length 7. Numeric value of the vector components represent daily caloric intake in the food groups of fruits, vegetables, grains, meats, dairy, oils and sugar. For every item in the food balance sheet (that is assigned a parent food group), data for food supply quantity (in kilograms per capita per day) and food supply (kcals per capita per day) is provided simultaneously for a country at a year. This helps in evaluating the energy to mass conversion factor for a food item j in a country i at a year t. Let k be a food group and I_k be the set of items listed under the food group k. We define the set of food groups as G (and $k \in G$). D_k is the per-capita daily calorie intake of food group k, as defined by the diet $\mathbf{D}$. We represent the food supply data for an item j in i at t as $f_j^{i,t}$. Then, the per-capita calorie intake of an item $j \in I_k$, in i at t, $d_j^{i,t}$, can be evaluated as the following:

$$d_j^{i,t} = D_k \cdot (f_j^{i,t} / \sum_{j \in I_k} f_j^{i,t})$$

If the food supply quantity of an item j in i at t be represented as $s_j^{i,t}$, then the kilocalorie to kilogram conversion factor in i at t, $c_j^{i,t}$, can be evaluated as follows:

$$c_j^{i,t} = \frac{s_j^{i,t}}{f_j^{i,t}}$$

The yearly mass demand, $R_j^{i,t}$ of item j in i at t, in tonnes, would then be:

$$R_j^{i,t} = d_j^{i,t} \cdot P^{i,t} \cdot 365 \cdot \frac{c_j^{i,t}}{1000}$$

Where $P^{i,t}$ is the population of the country i in year t. Note that here we have made the following assumption: for any arbitrary dietary intake of a food group k (say D_k), the distribution of D_k across the group items maintains the same proportion to that of the reported data. That is, if the average caloric intake of bovine meat in USA in 1980 was $1/4^{th}$ of the total calorie intake of meats (let's say 500 kcals/capita/day), then any other dietary intake, D_k, for meats, would have $1/4^{th}$ of it dedicated to bovine meat (in USA, in 1980).

Now, we define another conversion factor C_j called the source conversion factor for a food item j. The source conversion factor is independent of the country or the year (hence it does not have the superscripts i and t). A source conversion factor converts the mass of a food item to an equivalent mass of its source item. For most items this conversion factor is 1. However, for items like beer, wine, butter etc, the value is not unity. For example, source of beer is barley and its mass conversion factor is 4.78. To generate 1 tonne of beer, 4.78 tonnes of barley is required, on average.

The food balance sheet reports data for the Domestic Supply Quantity (in tonnes) and the Import Quantity (in tonnes) of every food item j into a country i at a year t. The Import Quantity data element, $I_j^{i,t}$, indicates the amount of the food item j that was imported into i in year t. The Domestic Supply Quantity data element, $D_j^{i,t}$, indicates the amount of j that is available to the population of i at t for domestic utilization. The ratio of Import Quantity to Domestic Supply Quantity is defined as the import dependency ratio, IDR, of j in i at t - $IDR_j^{i,t}$. That is,

$$IDR_j^{i,t} = I_j^{i,t} / D_j^{i,t}$$

The quantity j's source that comes in through import to meet the dietary demand of i at t is then,

$$I_{j,F}^{i,t} = \frac{IDR_j^{i,t} R_j^{i,t}}{C_j}$$

Similarly, the quantity j's source that comes from within the borders of i to meet the dietary demand of i at t is given by:

$$D_{j,F}^{i,t} = \frac{(1 - IDR_j^{i,t}) \cdot R_j^{i,t}}{C_j}$$

The units of $D_{j,F}^{i,t}$ and $I_{j,F}^{i,t}$ are in tonnes (per year). $Y_j^{i,t}$ and $\bar{Y}_j^{t}$ are defined as the yield of source of j in i and the average yield of source of j in the world respectively in t. Methods for calculating these are not included in this Supplementary Information document. For more information on it we advise the reader to check the Supplementary Information of [78]. In this thesis, the methods for calculating yields for food items are covered in Section 1.5.1. The units of these variables are in tonnes per hectare. Then, the expected land required globally to produce the demand for item j in i at t is:

$$L_j^{i,t} = \frac{D_{j,F}^{i,t}}{Y_j^{i,t}} + \frac{I_{j,F}^{i,t}}{\bar{Y}_j^{t}}$$

Hence the total global land required to produce the average dietary demand $\mathbf{D}$ for a country i in t is:

$$L^{i,t} = \sum_{k \in G} \sum_{j \in I_k} L_j^{i,t}$$

A.3 Results of parameter fitting

The results for the parameter fitting process for six select countries are summarized in table A.2. Figures B.3 and B.4 respectively show the model fits in the per-capita scale and the total land-use scale.

In Figures B.5, B.6, B.7 we see a global heat map for the rescaled parameters κ_i, σ_i and the parameter h_i for 166 of the currently existing countries in the world. The countries in colour grey are the ones for which parameters are not estimated. Figure B.8 is the global heat map for the ratio $m_i^0(t_r^i)/m_i(t_r^i)$. t_r^i is the year when living wage or minimum wage was reported. Note that these heat-maps show estimated parameters in their logarithmic form, i.e in log base 10 scale. In section A.4 we list the countries that were chosen for our analysis. The reason for inclusion and exclusion of countries in the analysis are also explained in section A.4.

Country Name (i)	Start Year t_0^i	End Year t_f^i	m_i^0(2018) (USD)	$log_{10}(\kappa_i)$	$log_{10}(\sigma_i)$	$log_{10}(h_i)$	$x_{0,i}$
United States of America	1961	2013	18262	-11.98	10.09	-2.61	0.65
China	1961	2013	3600	-11.88	10.20	-2.30	0.74
India	1961	2013	1500	-12.00	9.82	-0.1	0.79
Russian Federation	1992	2013	4734	-11.34	8.00	-3.03	0.68
Brazil	1961	2013	5114	-11.77	10.20	-1.95	0.86
Australia	1961	2013	12600	-11.52	0.016	-1.61	0.58

Table A.2: Model estimated parameters for six select countries. Per capita land use model is fitted to data.

At 2013, we achieve 1.24 % error, globally, from our model. That is, summed over the 166 countries we estimate parameters for, our model output is 1.24 % deviated from the global land use data in 2013.

In Figure B.12, absolute model errors are shown year-wise in a box-whisker plot. Statistics of absolute percentage error of the country-level model output relative to data is plotted. At 1961, error is zero due to our parameterization procedure (see Section A.1.4). Average absolute errors are always bounded between 0 % to 10 %. At 2013, average absolute percentage error is around 5% but global error is 1.24% as errors of several countries cancel each other.

A.4 Countries included in the analysis and discussions

A total of 180 countries are listed by the FAO Food Balance Sheet, 2013 [32]. These consist of both currently existing countries and countries that have ceased to exist (e.g USSR). Out of these 180 countries, parameter fitting was done for 166 countries - all of which are currently existing. The countries that were excluded because they no longer exist are - USSR, Yugoslavia SFR, Former Sudan, Ethiopia PDR, Serbia and Montenegro, Czechoslovakia, Netherlands Antilles and Belgium-Luxembourg. Currently existing daughter nations of these formerly existing countries are fitted for parameters instead. The DPRK is excluded because our source does not provide any food consumption data for it. Since our sources provide no per capita income data for Taiwan, it was eliminated for parameter estimation process too. The countries Saint Kitts and Nevis, Bermuda, Dominica, Antigua and Barbuda, Kiribati, Grenada and Saint Lucia are excluded because they have no model projections for population and income till 2100. OECD Env-Growth [26] is one of the models that is complied in the IPCC SSP Projection database for population and income. Since we use projections for per capita income and population from this model in our land use projection model, the aforementioned seven countries are excluded.

The time series for total global land use due to consumption (evaluated as the yellow time series in Fig B.1) was calculated yearly for all years between 1961 to 2013. It accounts for land consumed by all 180 countries minus Taiwan and Yugloslavia SFR. This calculation is done using the model in [78] and it accounts for the periods of existence of nations.

In Figures B.5, B.6, B.7 and B.8 we see global heat maps for the parameters of 166 nations. The countries for which parameters are not estimated are coloured in grey. Note that countries such as Papua New Guniea, DRC, Somalia, Syria and Libya are marked grey because consumption data for them are not reported by the UN FAOSTAT Food Balance Sheet, 2013 [32]. That is, they do not belong to the initial set of 180 countries.

We project for 164 countries out of the 166 countries that have been parameterized. The countries that are eliminated from the projection analysis are French Polynesia and New Caledonia.

A.5 Methods for projection analysis

Land use projections are made till the year 2100. All projections begin from 2011. We provide country level land use projections yearly between the start and end year of projections. We project for 164 countries. We call this set of 164 countries I. Details about their choices are explained in Section A.4. We choose 2011 as the start year because all the 164 countries from our set exist as nations thereafter. One of the primary requisites for land use projection is the availability of country level scaled down projections of population and income. We use five population and income scenarios in our projection analysis. These scenarios have been pre-defined in [77] and are popularly known as the IPCC SSP scenarios. All of the five scenarios under SSP (SSP1-5) have country level population and income projection through an ensemble of models. For our purpose, we use the projections under the model OECD Env-Growth [26]. The projections for population and income are available from 2010 to 2100 at an interval of 5 years. We use spline interpolation of order 3 to interpolate projected values of income and population between the 5 year intervals. Story line description of these SSP scenarios are available in [77].

A.5.1 Future yield (f) scenarios

Let c be the concerned time series, defined between 1961 to 2013, that we wish to project till 2100. The series c can either be $c^{U,max}$ or c^S for a country i. 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 is 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:

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

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

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

In Figure B.9, we show two examples of $c^{U,max}$ and c^S projection till 2100 using the above method. The two countries that are chosen are USA and Netherlands. USA shows a decreasing initial trend whereas Netherlands shows a initial increasing trend.
Intuitively, if the trend is decreasing, a f scenario implies that both $c^{U,max}$ and c^S can, at lowest, be f times their 2013 value. Similarly, for an increasing trend, a f scenario means that $c^{U,max}$ and c^S can be at most $1 + f$ times their 2013 value. The rates at which they approach these bounds are determined by their historical trend from 1990 to 2013.

A.5.2 Projection Methods, Continents and Parameter Planes

Mathematically, the projection model is the coupling of the country level model of all the countries i in I. That is, equation A.1, A.2, A.3 and A.4 taken together for all i in I represent our projection model. Equations A.1, A.2 and A.4 of every i is coupled to all other countries in I through equation A.3. We start projecting from 2011 and continue till 2100 while making yearly projections.

We work with 5 continents in our work. They are Africa, Americas, Asia, Europe and Oceania. North, Central and South America are clubbed together into one as the Americas. There are 45, 30, 43, 38 and 6 countries in these 5 continent groupings respectively. Russia is considered to be in Europe. Turkey is considered to be in Asia. Continent division methodology was done based on FAOSTAT food balance sheet groupings.

In the parameter planes that we analyze in the main text, we vary κ, σ and h from their baseline values. For all of the parameter planes, we make increments to parameters by -100% to 200% of their baseline values. We assume that all the countries in the world experience the same change in social parameters while performing the parameter plane analysis.

Appendix B

Supplementary Figures - Future of Global Land Use and Sustainable Consumption with a Social Learning Model

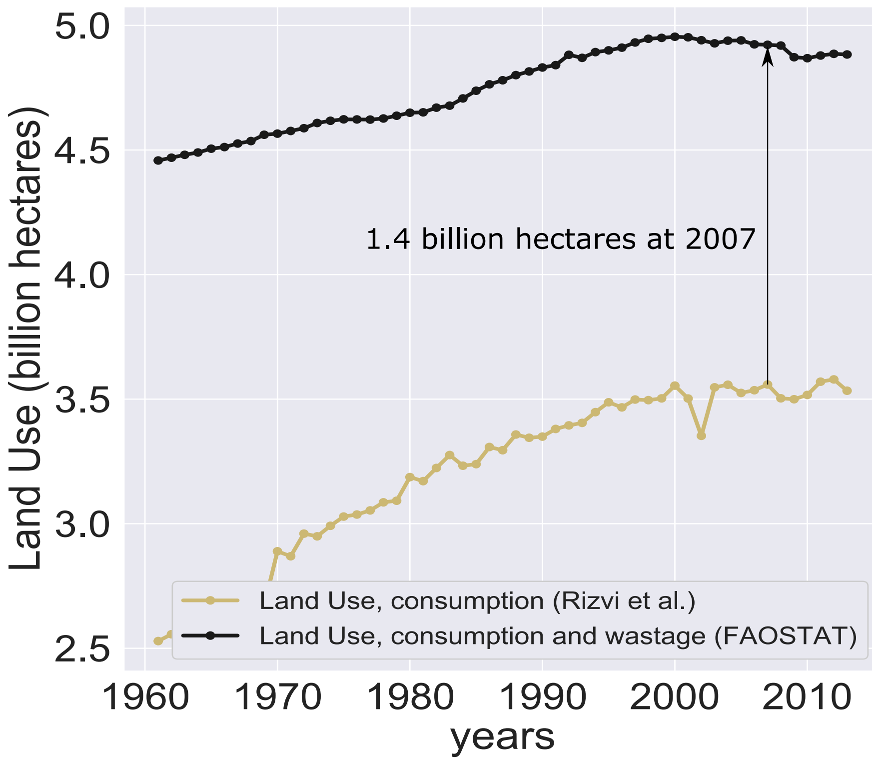

Figure B.1: Time Series data for Global Agricultural Land Use from 1961 to 2013. The yellow series is the data generated by the model in [78]. It accounts for the land that was spent for generating the food for human consumption. The black series is the data collected from [32]. It accounts for the land that was spent to generate the consumed food and the wasted food. We use the annual time series in yellow as $L^G(t)$ in the parameter estimation process.

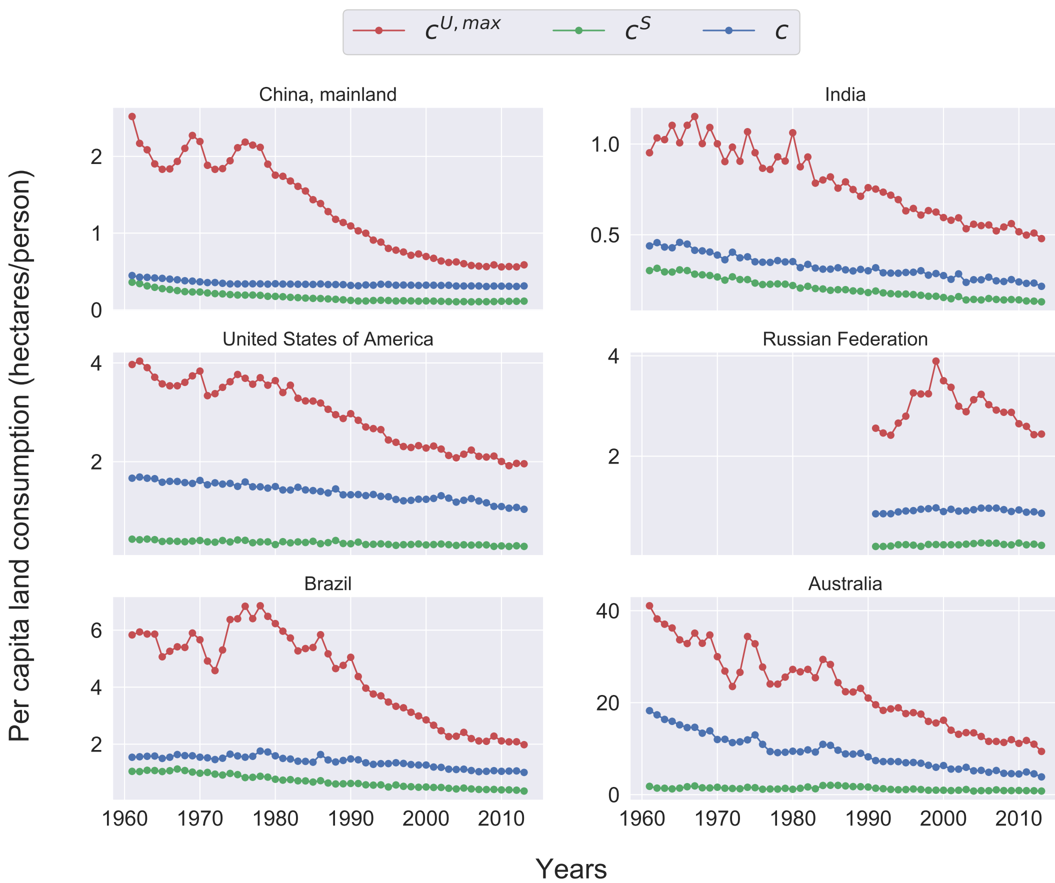

Figure B.2: The constructed time-series of $c^{U,max}(t), c^S(t)$ and c for United States, China, India, Russian Federation, Brazil and Australia using the method described in Supplementary Section A.1.1. $c^{U,max}$ is the maximum upper limit of per capita land use in a country. c^S is the per capita land use of sustainable practitioners in a population. c is the average per capita land use of a population. Time series are calculated using method in Rizvi et al. [78]. See Section A.1.1 for details.

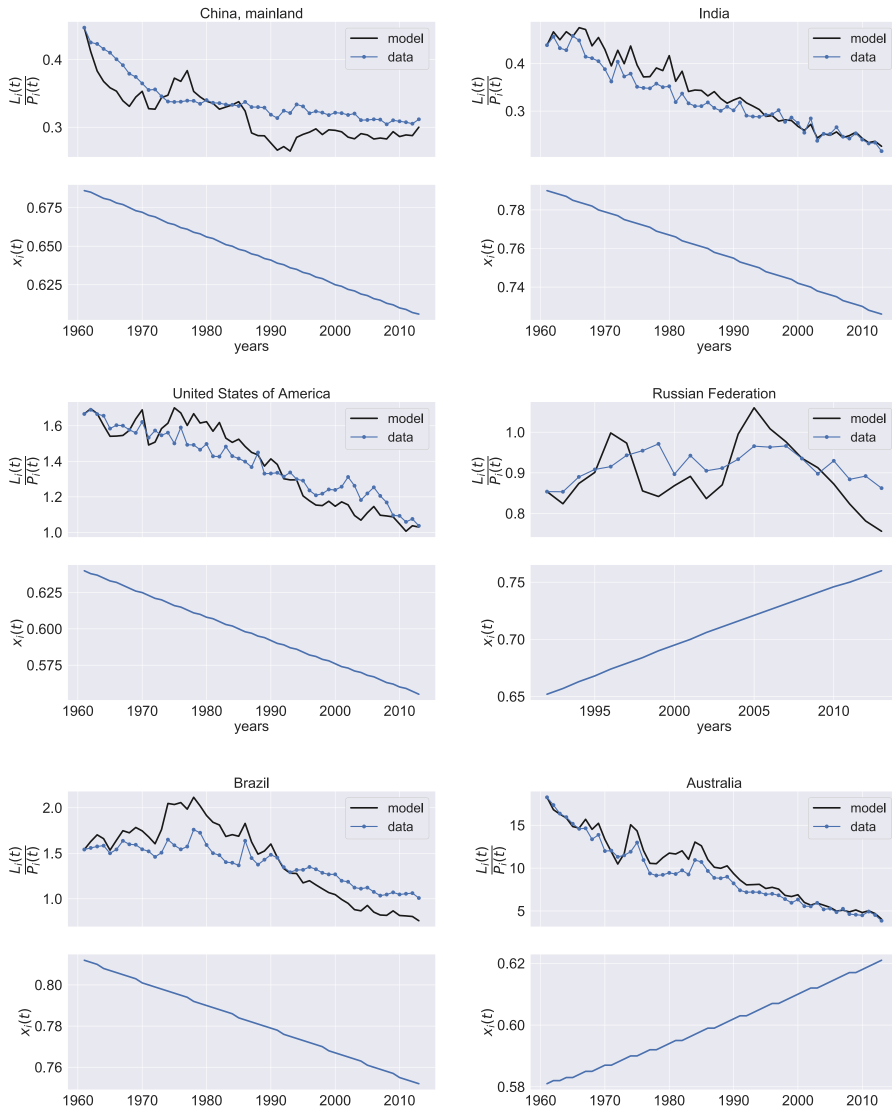

Figure B.3: Model fitted estimation and data for per capita land use in six countries along with model fitted estimation of fraction of sustainable diet practitioners over the time span between 1961 and 2013. The units of $L_i(t)/P_i(t)$ are in hectares per person.

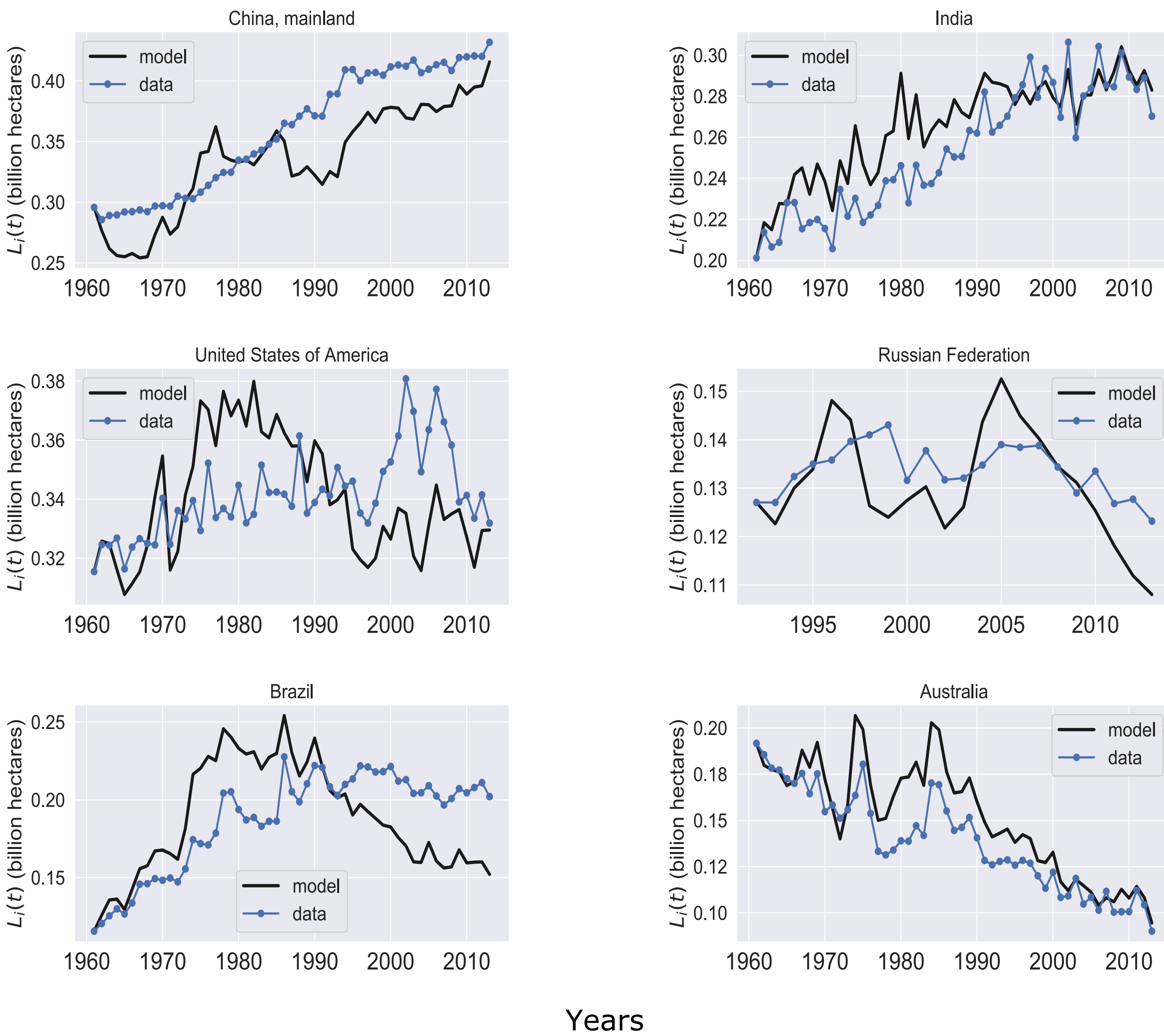

Figure B.4: Model Prediction and Data for total land consumed $L_i(t)$ due to food demand of countries for years from t_0^i to 2013.

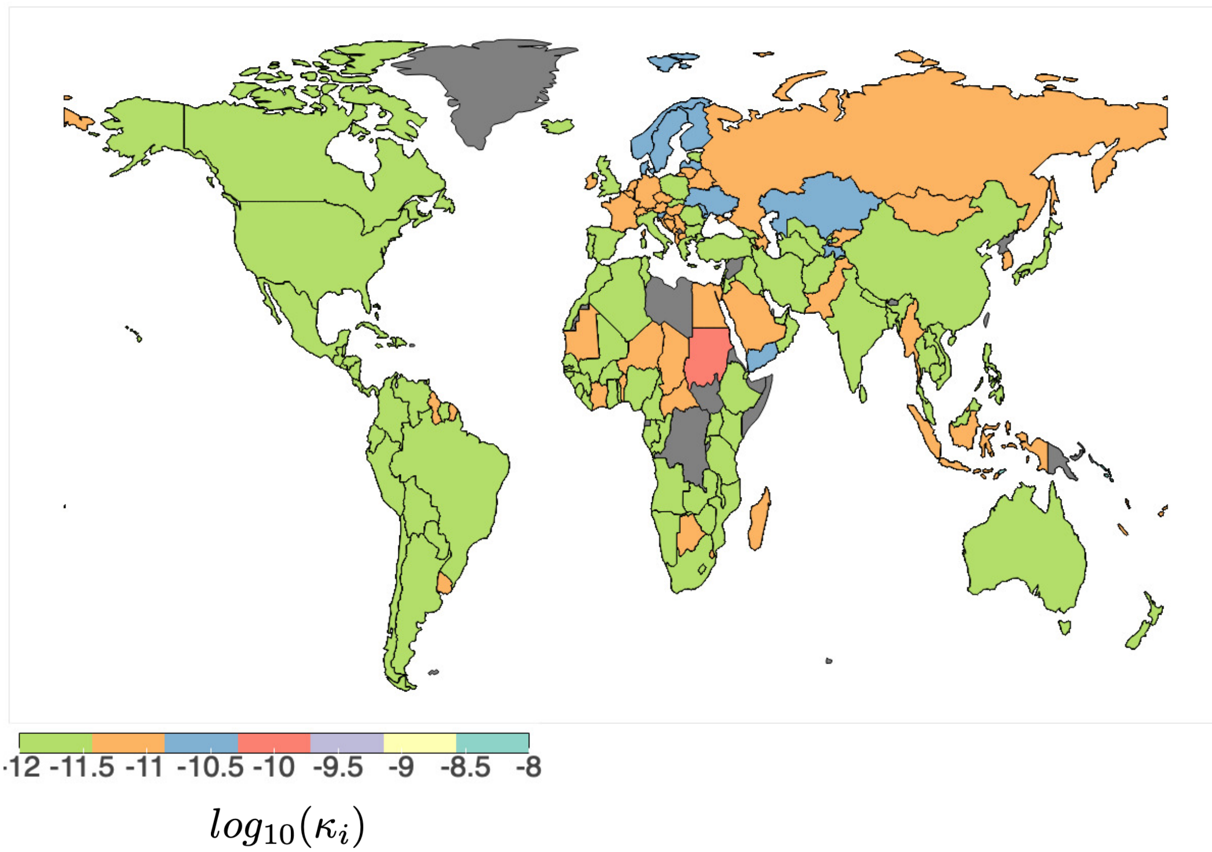

Figure B.5: Global heat map of $log_{10}(\kappa_i)$ values for 166 countries in the world. The countries in grey have not been estimated for parameters.

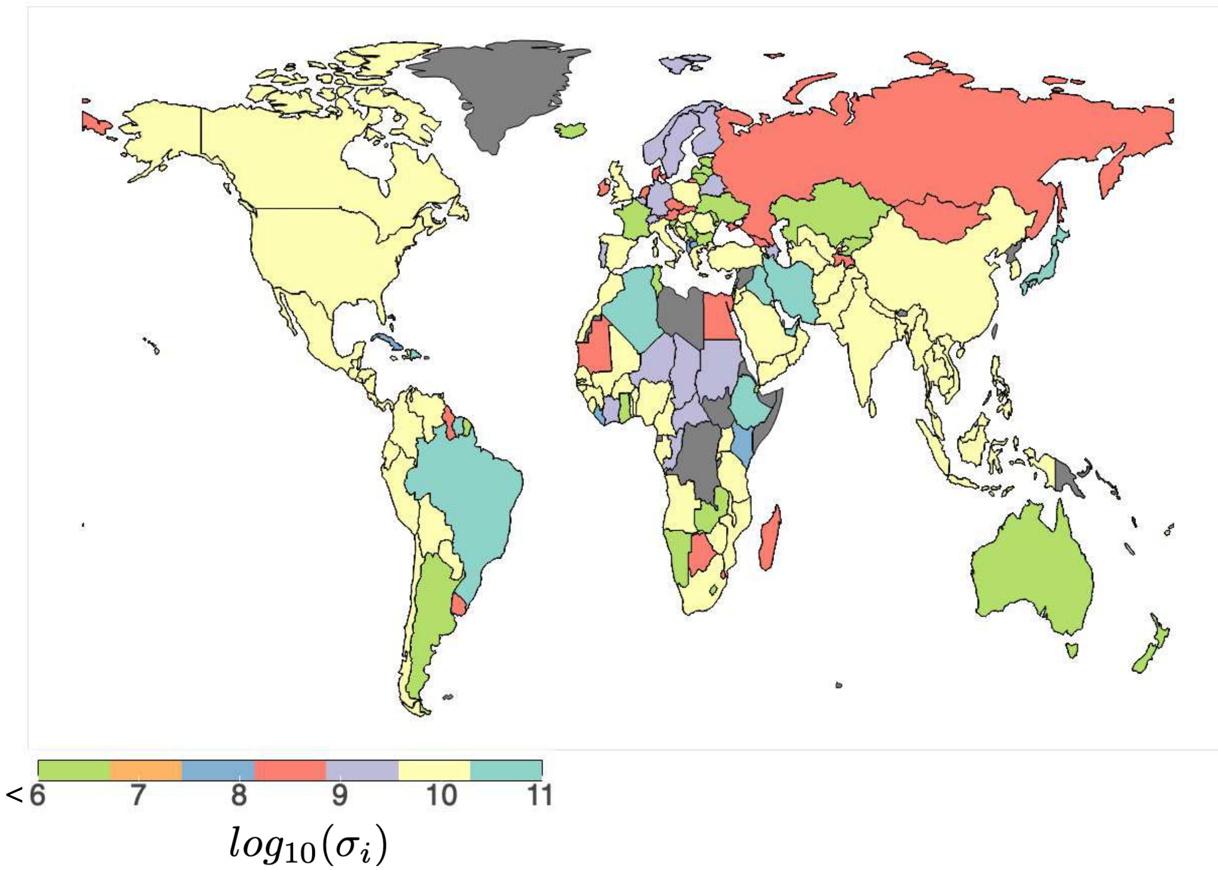

Figure B.6: Global heat map of $log_{10}(\sigma_i)$ for 166 countries in the world. The countries in grey have not been estimated for parameters.

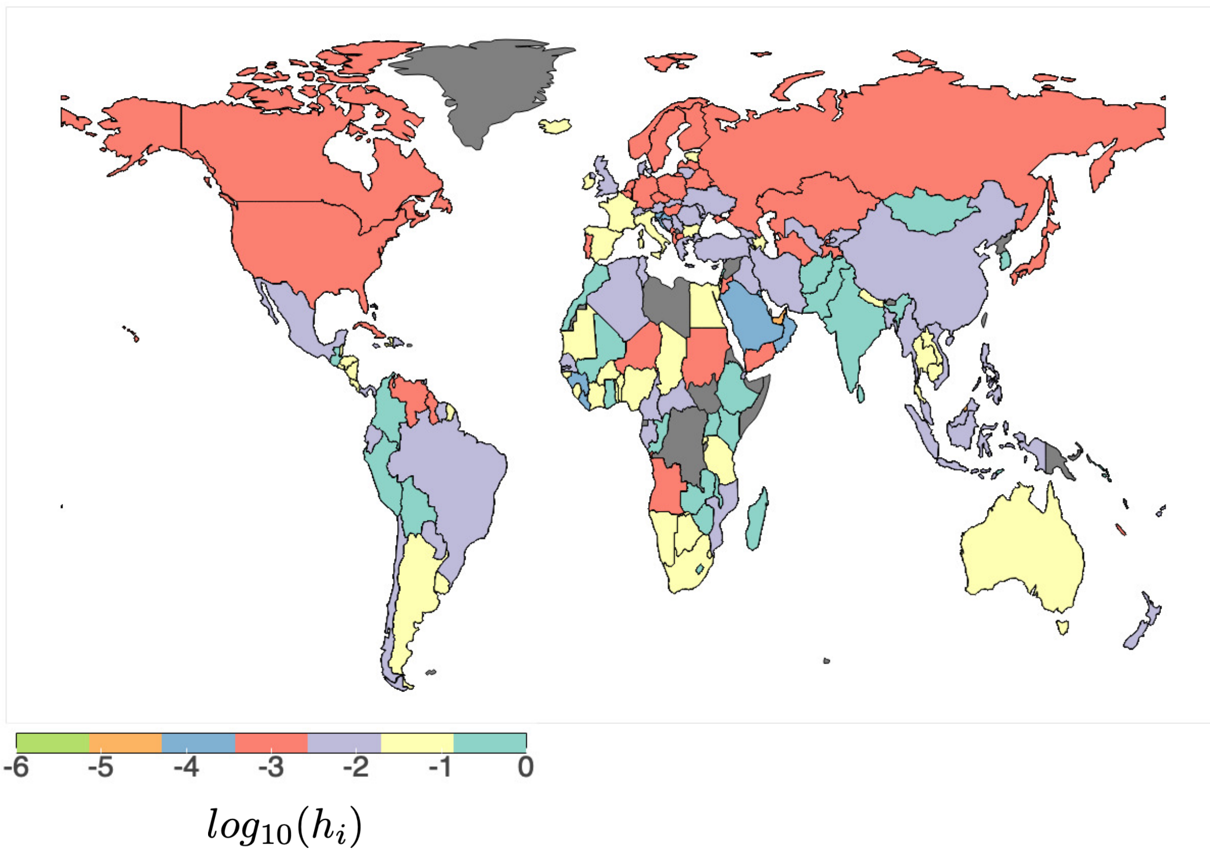

Figure B.7: Global heat map of $log_{10}(h_i)$ for 166 countries in the world. The countries in grey have not been estimated for parameters.

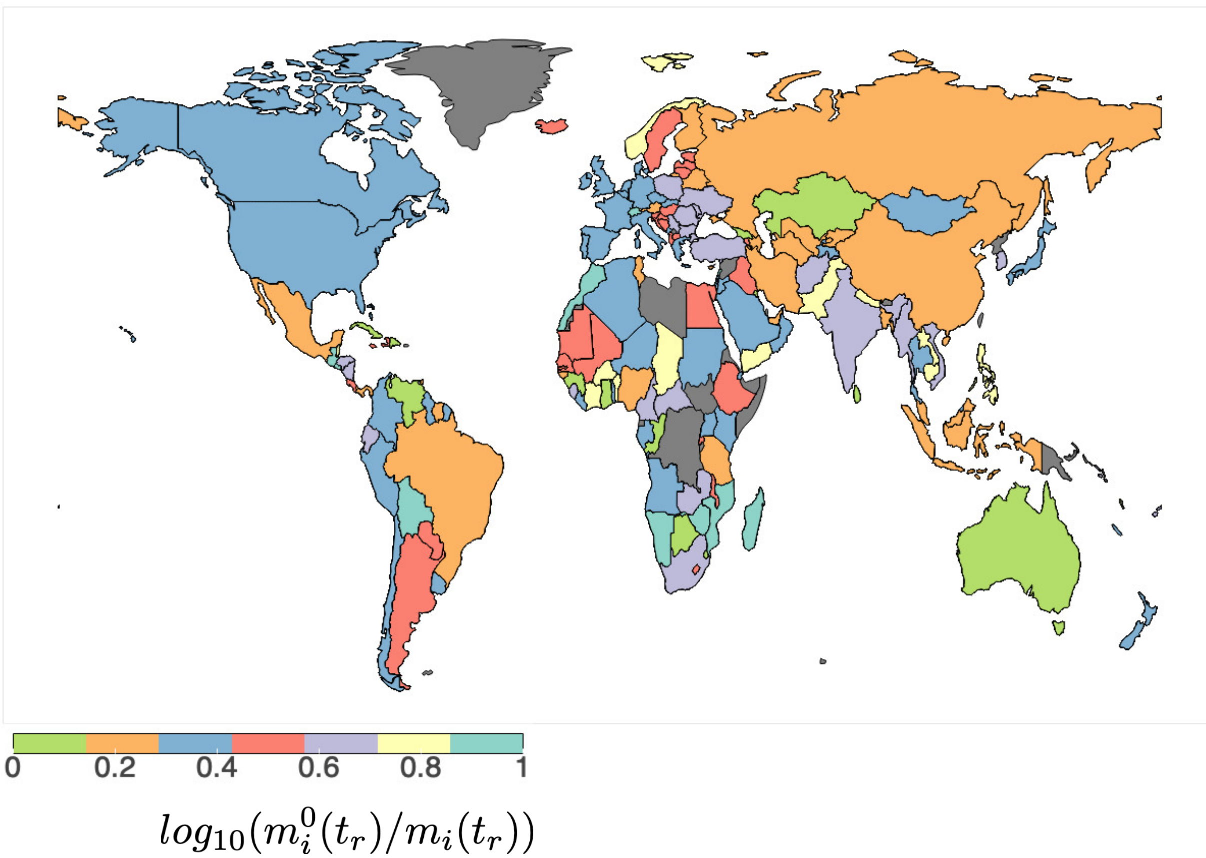

Figure B.8: Global heat map of $m_i^0(t_r^i)/m_i(t_r^i)$ for 166 countries in the world. t_r^i is the year when living-wage/minimum wage m^0 was reported. $m_i(t_r^i)$ is the average income of country i in t_r^i.

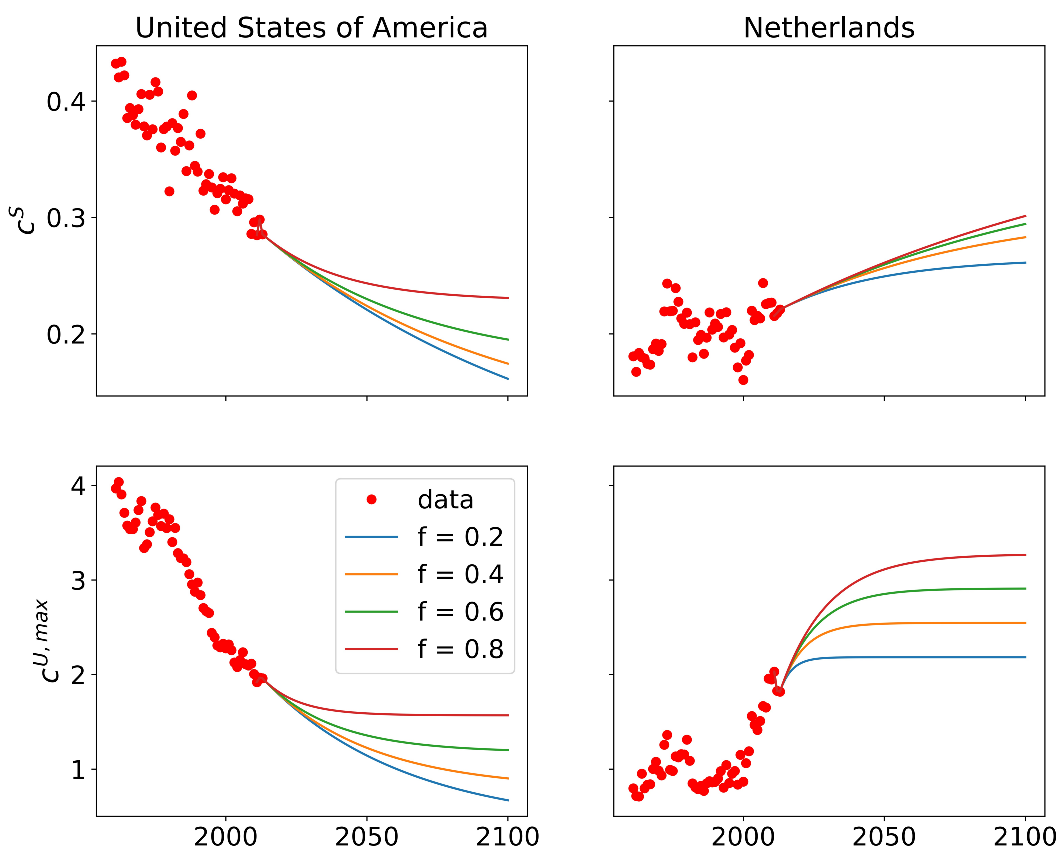

Figure B.9: Projections of $c^{U,max}$ and c^S for USA and Netherlands till 2100 under f scenarios. USA has an initial decreasing trend while Netherlands has an initial increasing trend. In this plot, results for f scenarios 0.2, 0.4, 0.6 and 0.8 are shown.

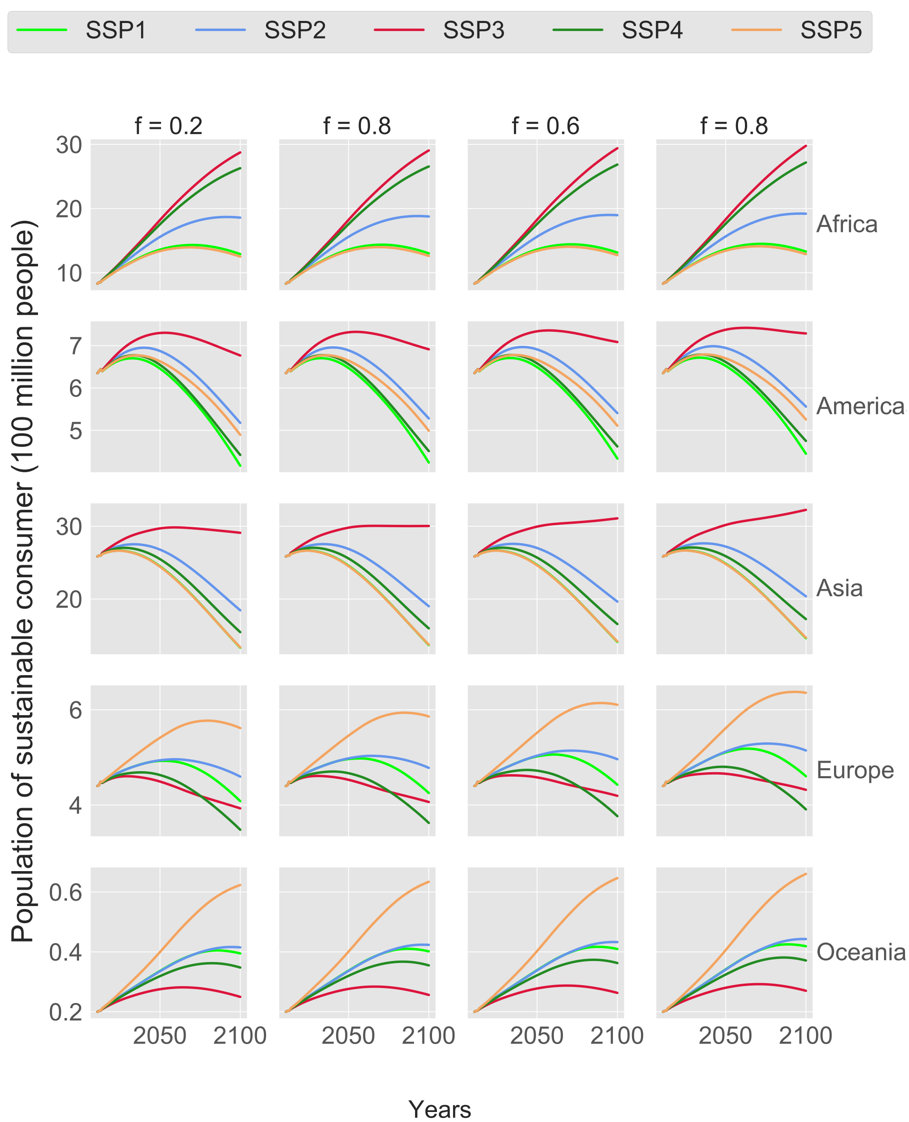

Figure B.10: Model projections for number of people consuming sustainably in the 5 regions from 2011 to 2100 under 20 scenario combinations. At the continental level, increase (or decrease) in sustainable consumer fraction does not imply increase (or decrease) in the population of people consuming sustainably.

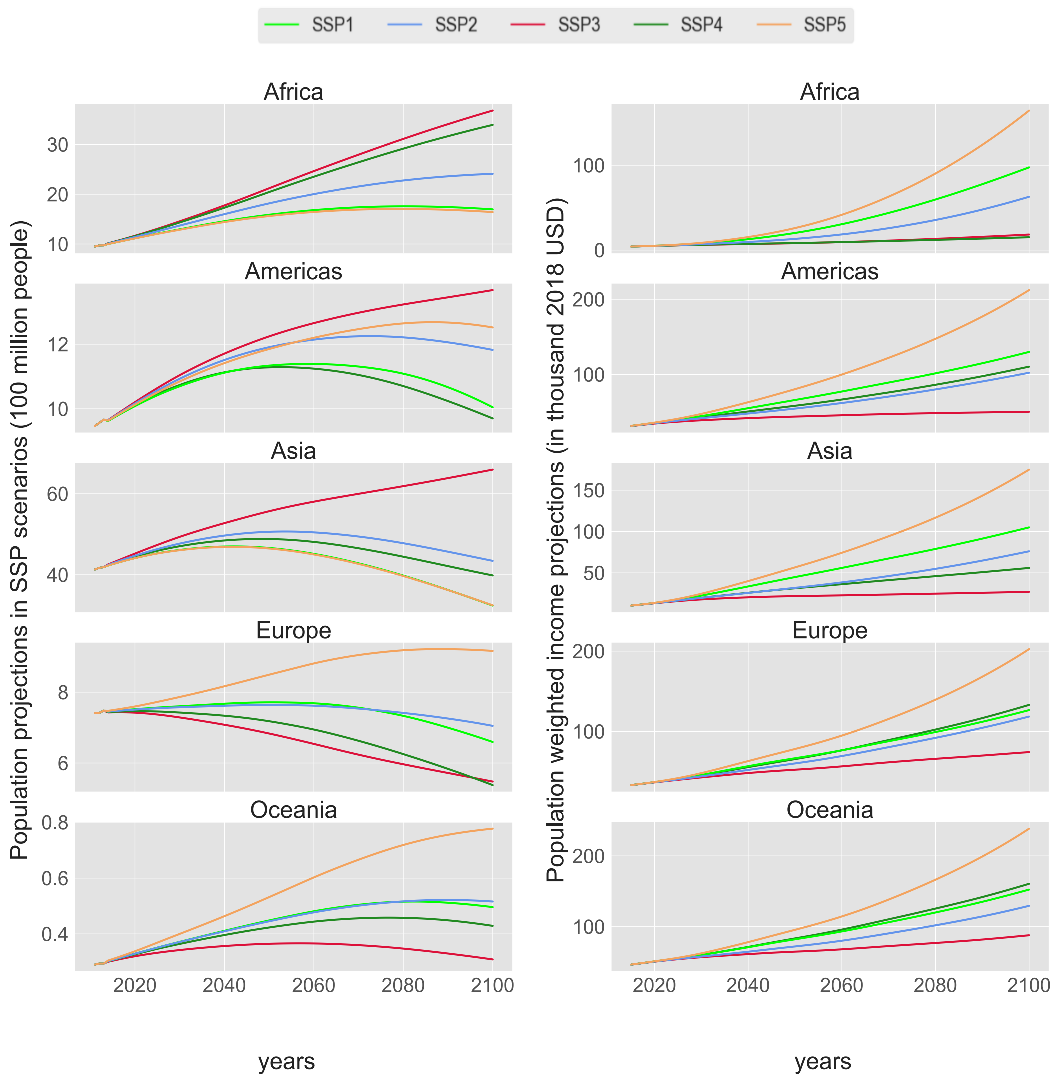

Figure B.11: Population and income projections under SSP scenarios for five distinct geographical regions. Income projections are calculated by taking population weighted average of country level projections. SSP3 shows lowest income growth while SSP5 shows the highest. For Europe and Oceania, SSP3 shows lowest population growth whereas it shows highest population growth for Africa, Asia and the Americas. Segregation of continents (regions) are done based on the FAOSTAT database.

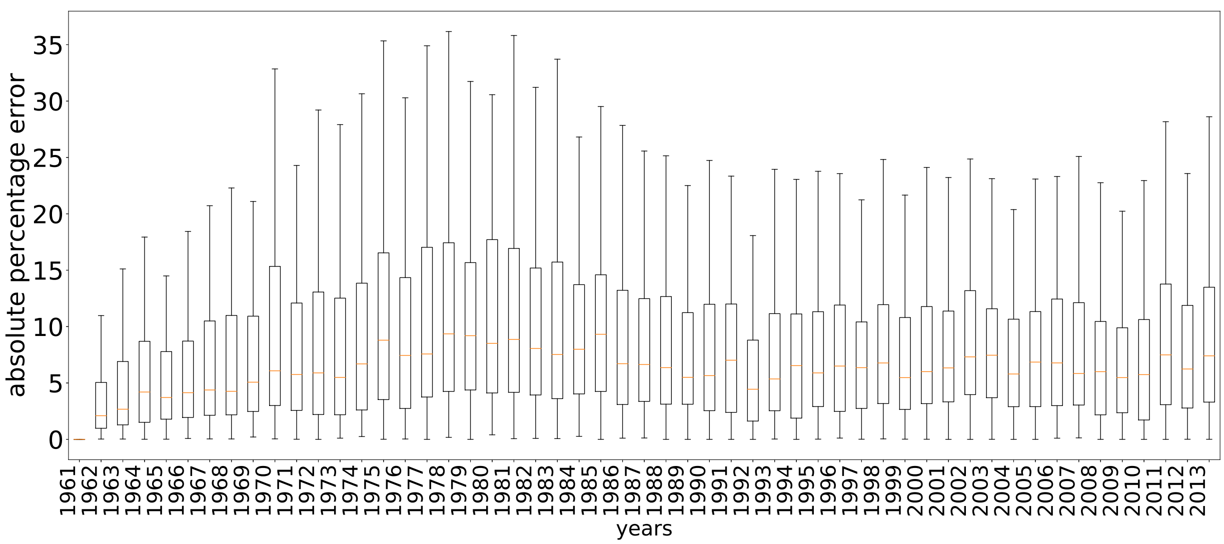

Figure B.12: Box and whisker plot showing absolute error of country-level model output with respect to data over the years from 1961 to 2013. Average absolute errors always remain below 10%.

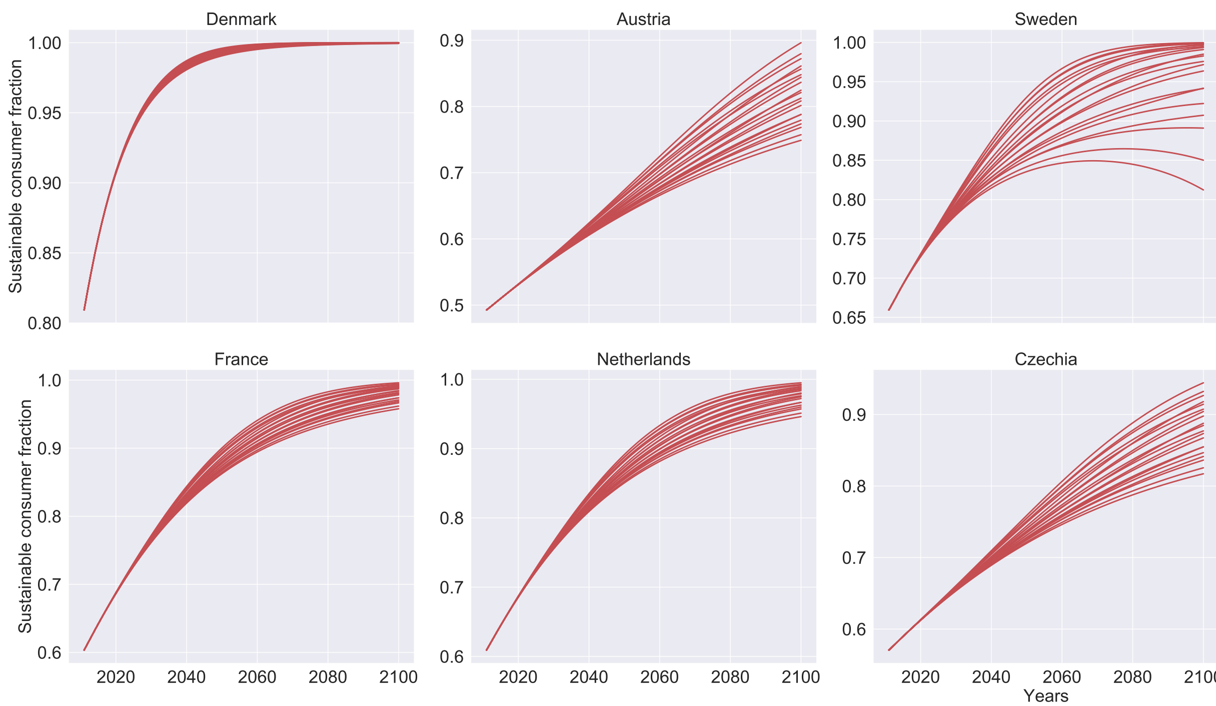

Figure B.13: Model projection of sustainable consumer fraction in six European countries that show relative increase in sustainable proportion in their population between 2013 and 2100 under baseline parameters. Results are shown for 25 scenario combinations (unlabeled).

Glossary

Crops data sheet Production Crops data sheet of the UN FAOSTAT data set 15, 18

Food Balance Sheet the Food Balance Sheets of the UN FAOSTAT data set 3, 5, 7, 10, 15, 17, 20

IPCC Intergovernmental Panel on Climate Change, a body of the United Nations 24

kcals an abbreviation for kilo calories 3

Land Use data sheet Land Use data sheet of the UN FAOSTAT data set 16, 19

Live Animals datasheet Live animals stock data sheet of the UN FAOSTAT data set 17

Livestock Primary datasheet Livestock Primary data sheet of the UN FAOSTAT data set 15–17

SSP Shared Socioeconomic Pathway scenarios. Released in the Fifth IPCC Assessment Report. 25

UN FAOSTAT the United Nations Food and Agricultural Organization dataset ix, 1, 3, 5, 10, 11, 15, 19

USDA United States Department of Agriculture 9