How diets affect human health and environmental sustainability

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Thesis Abstract

Dietary patterns are shifting to include more calories, processed foods, and animal products as populations become more affluent and urbanized. These dietary transitions have driven increases in diet-related diseases and environmental impacts. My thesis explores these links between diets, human health, and the environment – the diet-health-environment trilemma – and discusses and discusses what can be done to reduce the future impact that humanity's dietary choices are projected to have on human and environmental health.

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Introduction

Thesis Motivation:

I've had an interesting relationship with food. I love it - always have – but there were many times where I didn't eat a huge variety of foods. I was a horrendously picky eater growing up. My lunch for most of elementary and middle school was a corn muffin from *LeBoulanger* (a local bakery; the muffins are admittedly delicious), dinners were often mac-n-cheese (Kraft; not so tasty, I've since upgraded to Annie's), Pasta-Roni (essentially mac-n-cheese but with alfredo sauce; a bit better) or some other pasta dish, my breakfasts Eggo waffles or Honey Nut Cheerios, and my snacks often buttered toast topped with cinnamon and sugar (this is delicious; I still do it). I also didn't really eat meat, unless whatever I was eating was covered in sauce (e.g. hot dogs in mac-n-cheese; delightful childhood memories, but probably wouldn't recommend) or otherwise didn't taste much like meat.

Somewhere during my childhood my Grandma taught me to bake. We started with cookies (snickerdoodles first), and then slowly branched out into pies, cinnamon rolls, and breads. I baked most weeks, sometimes multiple times a week, and became interested in working in a bakery because of how much I enjoyed baking. I had an opportunity to do so in late 2013 (thanks Dave T for letting me go), and I quickly realized that I didn't actually want to work in a bakery.

Anyways, the whole point of this is to say that I love food. My love for food – making it, eating it, thinking about it – is a large part of why I research food and the impact that it has on human and environmental health. And in researching food, I've found that humans have a huge food problem.

Background:

It is undebatable that humanity's consumption of food is a major source – if not the single largest source – of global environmental harm. Our dietary choices are responsible for

~25% of GHG emissions (Vermeulen, Campbell, & Ingram, 2012); the crops and livestock grown to feed us occupy 40% of Earth's land surface (FAO, 2017); we use vast amounts of fertilizer to produce our food, which in turn results in nutrient pollution that has led to the formation of marine dead zones worldwide (Vitousek et al., 1997); and food production is the leading threat to biodiversity, threatening >70% of mammals and >80% of birds with extinction (IUCN, 2017).

Human diets are also the leading source of poor health globally and in most world regions. Undernourishment is still prevalent worldwide (affecting ~800 million individuals), yet diseases associated with overnourishment – obesity, heart disease, and diabetes, to name the three main ones – are becoming more prevalent everywhere (FAO, IFAD, & WFP; Forouzanfar et al., 2015). Organizations ranging from international (e.g. the World Health Organization) to local (e.g. Boynton Health) are combatting diet-related diseases; for example, through government dietary guidelines, education initiatives, and free access to food pantries. However, despite efforts to improve diet-related health outcomes, the ongoing and worsening global obesity and diabetes epidemics show that current efforts to improve dietary quality and reduce the prevalence of diet-related diseases are not always effective at improving human health.

It is becoming increasingly clear that human diets, human health, and environmental sustainability are interlinked. This diet-health-environment trilemma is global problem that will likely worsen with time: dietary shifts towards diets containing more calories, meat, dairy, eggs, and processed foods – shifts that occur globally as populations become more affluent and urbanized – are projected to be associated with decreased human health (e.g. a projected 50% increase in global diabetes prevalence from 2010-2030) (Euromonitor International, 2018) and increased diet-related environmental impacts (e.g. 50-80% increase in diet-related GHGs from 2010-2050) (Springmann et al., 2016; Tilman & Clark, 2014).

My research revolves around the diet-health-environment trilemma, identifying the current and projecting the likely future impact that our dietary choices will have on human and environmental health. My aim in researching these issues is to better inform and educate individuals and policymakers about the impact that our dietary choices have on human health and environmental sustainability so that we can lessen (or at least slow the decrease) the burden of the diet-health-environment trilemma.

The thesis:

My thesis has four chapters. The first chapter is a review and provides a perspective of the scope of the diet-health-environment trilemma. The second chapter examines how foods and food production systems (e.g. organic and non-organic) differ in their environmental impacts. The third looks at the associations between the health and environmental impacts of different foods, and the fourth forecasts how agricultural expansion will threaten biodiversity in Sub-Saharan Africa in the future.

Chapter 1: The Diet-Health-Environment Trilemma

The first chapter provides a perspective of the current and possible future extent of the diet-health-environment trilemma. It begins by highlighting how shifts towards diets higher in calories, animal products, and sugars and sweeteners have been associated with increases in diet-related diseases and diet-related environmental impacts. For instance, diabetes incidence in China increased from <1% to >10% between 1980 and 2008 as demand for animal-based foods in China increased >300% and demand for sugar and sweeteners increased >25%. Increases in diet-related diseases also occurred in other regions, and in particular in developing regions that underwent the most rapid dietary changes. These same dietary shifts have also resulted in large increases in diet-related environmental impacts – for instance, an ~90% increase in diet-related GHG emissions and an ~860% increase in nitrogen fertilizer applications.

The chapter continues by discussing how continued dietary transitions are likely to be associated with increasingly poor health and environmental outcomes. Diabetes

prevalence, for instance, is forecast to increase by ~55% between 2000 and 2030, with particularly large increases in developing regions. At the same time, diet-related GHG emissions are projected to increase by ~50-80% and cropland use by ~20-80%.

The chapter concludes by highlighting what we can do to make the diet-health environment trilemma less problematic. Forefront among these is adopting less meat-based diets which, if adopted globally, could reduce disease prevalence and diet-related environmental impacts below current levels. Increasing efficiency in food production (e.g. producing more food with fewer resources), reducing food waste, adopting regionally appropriate agricultural management strategies, and proactive land use planning could also help.

Chapter 2:
Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice

The second chapter examines the environmental impacts of different foods and of different food production methods. It was conducted by performing a meta-analysis on published life cycle analyses, which is an internationally recognized and standardized way of estimating the environmental impacts of a food production system.

In it I find that, per unit of food produced, that dairy, eggs, poultry, and pork often have environmental impacts an order of magnitude or more larger than the impacts of plant-based foods. Ruminant meat (beef, sheep, and goat) often have environmental impacts more than two orders of magnitude larger than plant-based foods.

This chapter also discusses the environmental impact of different food production systems – for instance, organic and conventional agriculture or grass-fed and grain-fed beef. Different food production systems often (but don't always) differ in their environmental impacts: organic foods and grass-fed beef require more land and result in more nutrient runoff than do non-organic and grain-fed beef, respectively. However, the

difference in environmental impact between different food production systems is often much smaller than the differences between foods.

The chapter concludes by highlighting how it would be more effective to reduce diet-related environmental impacts by changing diets rather than by changing the type of system in which a food is produced. Further, it discusses how the debate between organic and conventional foods – which is often viewed as either or – should instead be shifted to a conversation of how can we best develop a food system that integrates the beneficial aspects of organic systems with the beneficial aspects of non-organic systems.

Chapter 3:

Several analyses have shown that healthy diets often have low environmental impacts and diets with low environmental impacts are often healthy. However, because consumers often make decisions on individual foods and not entire diets, it is also important to understand the associations between the health and environmental outcomes of different foods. This chapter examines these associations by combining existing estimates on the health and environmental impacts of food consumption.

I find that minimally processed plant-based foods – whole grain cereals, legumes, nuts, fruits, and vegetables – are associated with improved health and have low environmental impacts; that chicken, dairy, and eggs are associated with no change in health outcomes and have intermediate environmental impacts; that red meat (pork, beef, sheep, goat) is associated with poor health and has large environmental impacts; and that sugars are associated with poor health but have low environmental impacts.

Chapter 4: Future agricultural land expansion will threaten biodiversity in Sub-Saharan Africa

Agriculture is the leading threat to biodiversity, threatening ~70% of mammals and ~80% of birds with extinction. Previous analyses have shown how agricultural expansion is projected to drive biodiversity decline across Sub-Saharan Africa. However, while these

analyses have made important contributions to our understanding of how agricultural expansion will likely threaten biodiversity, their utility for conservation planning has been limited by coarse spatial scales; a focus on a relatively small suite of species; or by investigating broad development pathways rather than changes to specific aspects of the food system.

This chapter expands on previous analyses by forecasting biodiversity outcomes at a spatial scale relevant to ecological processes and conservation action, by incorporating a larger selection of species in the analyses, and by examining the benefit to biodiversity if specific policy outcomes were to be achieved. I find that agricultural expansion is projected to drive a 14.2% reduction in remaining area of habitat by 2060 across all Sub-Saharan African bird species.

I also explore how reducing agricultural land expansion might be able to prevent projected biodiversity declines. Closing yield gaps, reducing meat consumption, or increasing trade patterns to shift production away from low-yielding areas, could independently avoid ~16-51% of declines in remaining habitat, while simultaneous adoption of all three scenarios is projected to prevent ~81% of declines in remaining habitat.

Conclusion

In its entirety, my thesis shows that global dietary transitions towards diets higher in calories, meat, dairy, eggs, and processed foods, when combined with population growth, will likely decrease human health and environmental sustainability. Instead, switching diets away from foods that are associated with poor health and have high environmental impacts and instead towards foods with better health outcomes and lower environmental impacts would likely improve diet-related human and environmental health.

Finding ways to shift diets in these ways will be difficult, but possibly necessary if we are to avoid large increases in poor health and environmental degradation. Taxes, education

initiatives, food labeling, and changes in the food environment have been successful at shifting diets to become healthier, and might also be effective at shifting diets to become more sustainable. Additionally, because effectiveness of these policies often increases through time, further implementation of these and other policies in the near future would likely maximize the chance of a healthier and more sustainable future.

Chapter 1: The diet-health-environment trilemma

Abstract:

Diets are shifting to be higher in calories, highly processed foods, and animal products as populations become more affluent and urbanized. These dietary shifts are driving increases in diet-related non-communicable diseases and are also causing environmental degradation. These linked impacts pose a new key issue for global society - a diet, health and environment trilemma. If current dietary trajectories were to continue for the next several decades, diet-related non-communicable diseases would account for three-quarters of the global burden of disease and also lead to large increases in diet-related environmental impacts. Here we discuss how shifts to healthier diets – such as Mediterranean, pescetarian, vegetarian, and vegan diets – could reduce incidence of diet-related non communicable diseases and improve environmental outcomes to help meet global sustainability targets. In addition, we detail how other interventions to food systems that use known technologies and management techniques would improve environmental outcomes.

Introduction:

Global agriculture and the global food production system are essential for human survival and prosperity, but also contribute to poor health and environmental degradation. Nearly 800 million people are undernourished globally and more than 2 billion people are overweight or obese (United Nations, 2017). Global agriculture emits ~25 – 33% of global greenhouse gasses (GHGs) (IPCC, 2014), occupies ~40% of Earth's terrestrial surface (FAO, 2017), is the single greatest cause of extinction risk globally (IUCN, 2017), is the major cause of eutrophication of freshwater and marine ecosystems because of fertilizer runoff (Vitousek et al., 1997), harms health through reduced global air quality (Bauer et al., 2016; Lelieveld et al., 2015), and accounts for over 70% of global freshwater withdrawals (Molden, 2007).

The links between diets, human health, and environmental degradation – known as the diet, health, and environment trilemma – comprise a series of interconnected problems confronting every society globally. Moreover, these problems are on a trajectory to become progressively more severe during the coming decades, especially in developing nations, because dietary shifts towards less healthy and less sustainable diets are tightly associated with increased affluence and urbanization. Also, because diets are socially, economically, and culturally important, solutions to the diet-health-environment trilemma must be consistent with the social, economic, and cultural values of each country or region.

In this review, we first summarize and evaluate the data that describe the magnitudes and trends of each of the three components of this trilemma: (1) the causes of dietary shifts over the past few decades and the associated health and environmental outcomes are one component, (2) the environmental and health impacts of different types of foods, and (3) the future human health and environmental harm that would result if current dietary trajectories were to continue into the future. Next we discuss the environmental and health benefits if healthier diets were to be broadly adopted globally. We then examine other aspects of the global food system, which if modified, would also reduce agriculture's health and environmental impacts. We end by highlighting recent food-related policy initiatives and their effectiveness in improving diet-related health and environmental outcomes.

Historic Dietary Shifts and their Health and Environmental Impacts

Per capita total caloric demand, measured as the amount of food per person that enters households, has increased since 1961 as populations have become more affluent and urban (Kearney, 2010; Figure 1). Increases in caloric demand have been the most rapid in developing regions that have undergone large increases in per capita GDP (FAO, 2017). For instance, per capita caloric demand has increased >50% to ~2540kcal/day in South and South East Asia and >30% in Latin America since 1961, for a total of ~2540kcal/day in South and South East Asia and ~3030kcal in Latin America. Per capita caloric demand

in Sub-Saharan Africa was fairly stagnant between 1960 and 1985, as was per capita GDP, but has increased by >20% since 1985 and is now ~2460kcal/day. In contrast, total caloric demand in countries that were already affluent in 1961 has been comparatively stagnant. Caloric demand in Europe, for example, increased ~13% to ~3200kcal/day. The United States is perhaps one exception to this otherwise global trend, having experienced an ~30% increase in caloric demand (~800 kcal/day) between 1961 and 2000, although caloric demand in the United States has decreased 70kcal/day over the past decade to ~3680 kcal/day in 2013 (Fig 2a).

Demand for animal-based foods (meat, fish, milk, and eggs) has followed similar trends since 1961, with the largest increases in consumption in low- and middle-income nations and smaller changes in higher-income nations. Of particular note is the 1300% increase in demand of animal-based foods in China, an increase from 52kcal/day in 1961 to 724kcal/day in 2013. Demand for animal-based foods in East Asia increased by ~400% to ~700kcal/day, while demand in Latin America and the Caribbean increased by ~75% to ~710kcal/day. Consumption of animal-based foods is increasing at a slower rate in Sub-Saharan Africa, having increased ~17% to ~190kcal/day over the same time period. Consumption trends of animal-based foods in high-income nations vary. For instance, consumption of animal-based foods decreased ~ 15% in Oceania and ~5% in North America but increased by over 20% in Europe. Consumption of animal-based foods in Oceania, North America, and Europe is now ~1000kcal/day, ~970kcal/day, and ~970kcal/day, respectively.

Demand for sugars and sweeteners has increased rapidly in most world regions. Demand in Eastern Asia has increased >150% since 1961 and is now ~90kcal/day while demand in Northern Africa, Sub-Saharan Africa, and South and South East Asia has increased > 50% to ~300kcal/day, ~130kcal/day, and ~210kcal/day, respectively. Demand for sugars and sweeteners in most other regions has increased between 15 – 40%, although demand in Oceania and Northern Europe has decreased by ~24% and ~20%, respectively. Current demand for sugars and sweeteners is highest in North America (~580kcal/day),

Mesoamerica (~450kcal/day), North Asia (~430kcal/day), and South America (~410kcal/day).

Per capita demand for fresh fruits and vegetables has increased in all world regions except Western Asia. The largest proportional increase in demand for fruits and vegetables was in South and South East Asia and Northern Africa, which experienced a ~200% and ~150% increase, respectively. Eastern and Northern Europe also had rapid increases in demand for fruits and vegetables. Vegetable demand in Sub-Saharan Africa and Latin America and the Caribbean, regions where the average individual consumes less than one-third the fresh vegetables of any other region, was relatively stagnant. Current (2013) demand for fresh fruits and vegetables is lowest in Sub-Saharan Africa, Latin America and the Caribbean, and Eastern Europe.

Changes towards diets higher in total calories, animal-based foods, and sugars and sweeteners have been associated with increased prevalence of diet-related non-communicable diseases such as diabetes, heart disease, and overweight and obesity (Figure 1d). Over the past several decades, diet-related diseases have increased in all world regions but have increased at the fastest rate in regions where dietary shifts and lifestyle changes have been the most rapid.

Diabetes prevalence has increased in all world regions (Ezetti et al., 2016). Between 1980 and 2014, the percent of the global adult population suffering from diabetes increased from 4.7% to 8.5% (Ezetti et al., 2016; World Health Organization, 2016). Diabetes prevalence increased most rapidly in those countries that have undergone rapid shifts towards diets higher in sugars and animal-based foods. For instance, diabetes prevalence in China increased from <1% to >10% between 1980 and 2008 as demand for animal-based foods increased by ~300% and demand for sugars and other sweeteners increased by ~25% (Hu, 2011). Diabetes prevalence has also increased 150% in the Middle East and North Africa (from ~5% in 1980 to ~12.5% in 2014), 100% in Central Asia (increase from ~5% in 1980 to ~10% in 2014), and over 50% in Southern Africa

(from ~4% in 1980 to 7% in 2014) and the Caribbean (from ~5% in 1980 to ~8% in 2014). Furthermore, the rate of increase of diabetes prevalence has itself been increasing in many of these regions in the last 5 – 15 years.

The prevalence of overweight and obesity has also increased rapidly. Global prevalence of overweight (classified as a body mass index (BMI) > 25) and obesity (BMI > 30) increased ~30% - from 29% to 37% of the global adult population - from 1975 to 2014 (Ng et al., 2014). The increase in overweight and obesity has been especially rapid in developing regions such as South and South East Asia (~250% increase in prevalence since 1975 to ~20% of the adult population being overweight or obese in 2013), East Asia (~180% increase to ~30% of the adult population), and Sub-Saharan Africa (~150% increase to ~27% of the adult population). Overweight and obesity prevalence is increasing at a less rapid rate in high-income and developed regions, although the current prevalence of overweight and obesity is higher in these regions than in less affluent and developing regions. For instance, overweight and obesity prevalence increased ~50% in Europe and ~60% in North America, with ~58% of the adult population being overweight or obese in Europe and ~66% of the adult population being overweight or obese in North America (Fig 2b).

The recent increase in diet-related diseases has caused the global burden of disease to shift from diseases associated with infection and under-consumption to diseases associated with over-consumption and unhealthy diets. Diseases associated with over-consumption are now the leading source of poor health globally and in most of the world's geographic regions, accounting for ~40% of the global burden of disease and higher proportions in developed regions that have a history of over-consumption (Forouzanfar et al., 2015). Furthermore, prevalence of diseases resulting from overconsumption is increasing – even in regions where under-consumption is still widespread (Abdullah, 2015) – and will likely continue to do so if recent dietary transitions continue (Euromonitor International, 2018; Springmann et al., 2016).

Shifts towards diets higher in calories and animal-based foods have also resulted in increasing diet-related environmental impacts. From 1961 to 2013, the amount of land used for crop production increased ~15%, agricultural GHG emissions increased ~90%, and nitrogen fertilizer application increased ~860% globally (Figure 2c; FAO, 2017). Runoff from the use of nitrogen and phosphorus fertilizers has polluted many large bodies of water (V. H. Smith, Tilman, & Nekola, 1999; Vitousek et al., 1997), while volatilization of nitrogenous fertilizers harms human health via formation of fine particulate matter ($PM_{2.5}$) (Bauer et al., 2016; Lelieveld et al., 2015). Atmospheric deposition of agriculturally-derived nitrogen also threatens terrestrial ecosystems and their plant diversity (IUCN, 2017; Vitousek et al., 1997). Global irrigation water withdrawals have also increased rapidly, while agricultural activities such as habitat destruction, habitat fragmentation, and fertilizer applications have led to agriculture becoming the leading threat to biodiversity globally, threatening ~70 – 75% of endangered birds and mammals with extinction (IUCN, 2017).

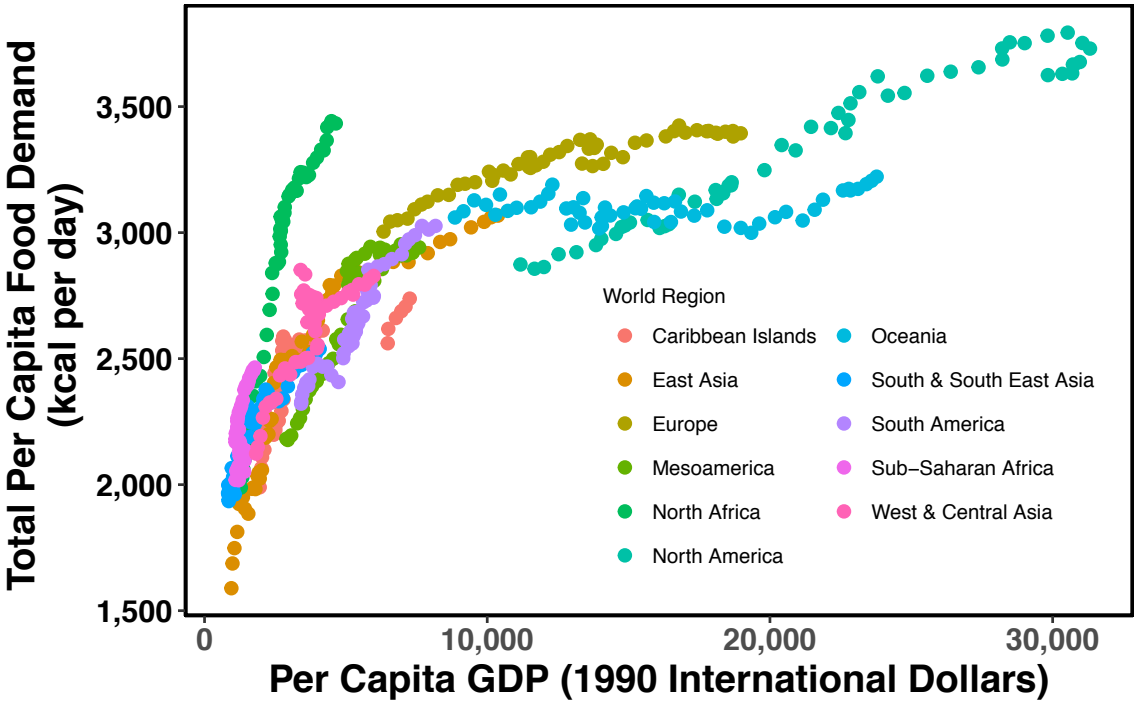

Figure 1: Relationship between per capita wealth and daily food demand. Data spans 1961 to 2013 and is aggregated into 11 world regions. Each point indicates per capita food demand and per capita GDP Purchasing Power Parity in a given year in a given world region. Per capita GDP Purchasing Power Parity is measured in 1990 International Dollars, which are an indication of per capita wealth after being adjusted prices in different countries. Per capita food demand is measured as the amount of food that enters the household per day. Per capita food demand is higher than per capita consumption because it does not account for household food waste. Per capita food demand data is from ref (FAO, 2017); per capita GDP Purchasing Power Parity is from Groningen Growth and Development Centre (2017).

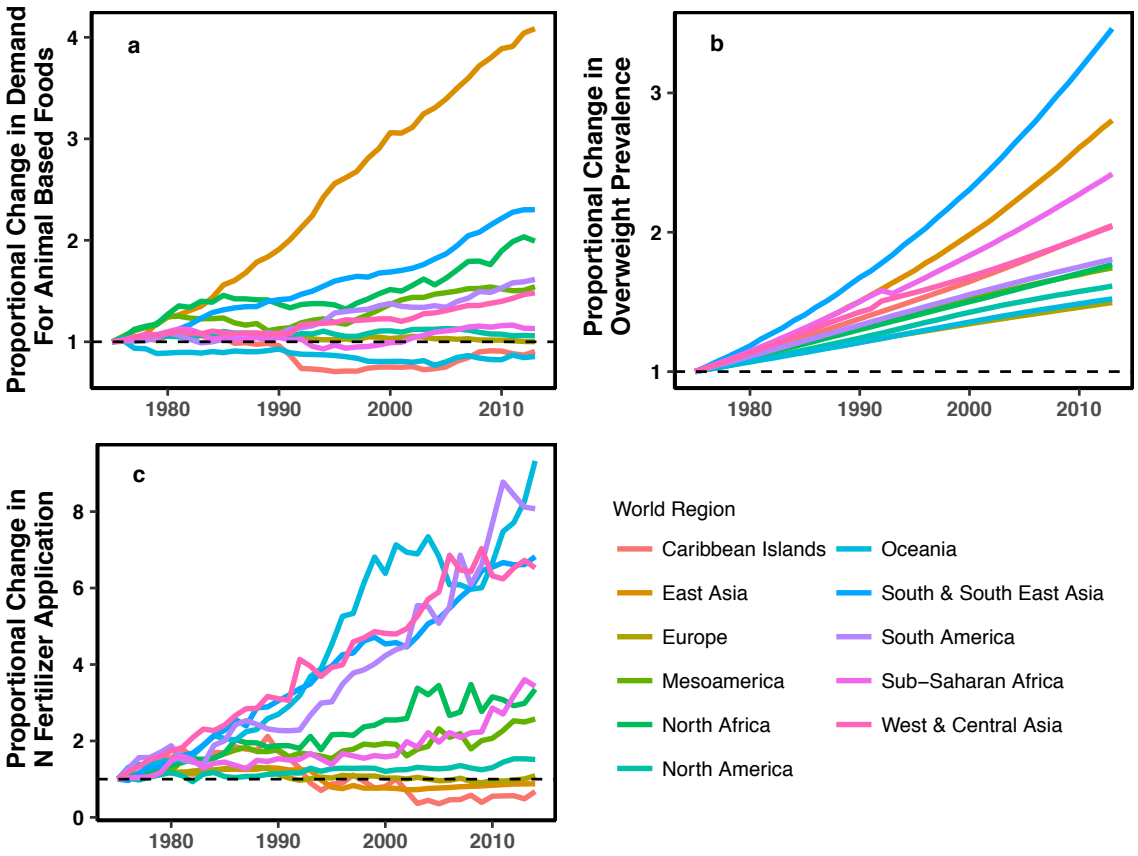

Figure 2: Historic trends in food demand, health, and environmental outcomes. Proportional increase, relative to 1975 (which is set at a value of 1.0) in **(a)** daily per capita demand for animal based foods (dairy, eggs, meat, and fish), **(b)** prevalence of overweight and obesity, and **(c)** application of nitrogenous fertilizers. Data for a and c is from FAO (2017). Data for panel b is from World Bank (2017).

Forecasts of Future Diets

Several analyses have forecasted future dietary patterns by examining historic relationships between per capita consumption and per capita income, urbanization, and several other determinants of dietary patterns (Alexandratos & Bruinsma, 2012; Tilman et al., 2011; Tilman & Clark, 2014). These analyses estimate that the global average per capita calorie demand, measured as calories that enter the household, will increase by ~11 – 15% from 2005 to 2050 (Alexandratos & Bruinsma, 2012; Tilman & Clark, 2014). Global demand for animal-based foods is expected to increase more rapidly, with meat demand expected to increase ~26 – 32% and dairy and egg demand expected to increase ~20 –58% by 2050. Shifts towards diets higher in calories and animal based foods are forecast to be particularly rapid in developing nations, especially those in South and Southeast Asia and Sub-Saharan Africa, because of the large expected proportional increases in per capita GDP in these regions. In contrast, dietary shifts are expected to be smaller in currently developed nations.

The combination of forecasts of growth in per capita food demand and in global population suggest that global crop production may increase by 60 to 100% from 2005 to 2050 (Alexandratos & Bruinsma, 2012; Pardey et al., 2014; Tilman et al., 2011). These estimates vary because of different assumptions about the growth of per capita meat demand and the extent to which pasturelands or grains would be used to produce dairy and ruminant meats. Alexandratos and Bruisma (2012), who forecast a 60% increase in global crop production, based their estimates on historic trends in national crop production and expert opinion and assume smaller increases in meat consumption and larger amounts of dairy and meat produced on pasturelands. Tilman et al (2011), in contrast, forecast a ~100% increase in global crop production by combining UN forecasts of 2050 populations for each country with historic global relationships between per capita wealth and per capita crop demand, which includes both the animal feeds and human

foods required to meet per capita food demand. Pardey et al (2014) forecasted that global crop production would increase by 69% from 2010 to 2050 to meet future dietary patterns.

Environmental and health impact of different foods

Environment:

Recent meta-analyses (Clark & Tilman, 2017; Clune et al., 2017; de Vries & de Boer, 2010; Nijdam et al., 2012; Tilman & Clark, 2014) of crop and food life cycle assessments (LCA) have elucidated the overarching patterns of environmental impacts of producing ~100 different foods across multiple environmental indicators. Here we review the results of these meta-analyses, discussing how GHG emissions, land use, and nutrient pollution vary between food types (Figure 3a). We mainly compare foods on the basis of their caloric or protein content, but note that comparisons of vegetables and fruits are best made in terms of servings.

LCA meta-analyses have found that plant-based foods have the lowest GHG emissions per unit of food produced per kcal of food produced; dairy, eggs, pork, poultry, and low-impact fish production systems (non-trawling fisheries and pond, net pen, and flow-through aquaculture systems) have GHG emissions ~100 – 2,500% higher than those of plant-based foods per unit of food produced; and production of high-impact fish (trawling and re-circulating aquaculture) and ruminant meats (beef, sheep, goat) has GHG emissions ~2,000 – 10,000% larger than those of plant-based foods per unit produced. The GHG emissions of fish productions vary because of their energy inputs. Wild-caught fish captured with lines, purse nets, and seine nets can have low energy inputs and relatively low GHG emissions as do unfed, pond, and net pen aquaculture systems. Trawling fisheries (where nets are dragged across the seabed) and recirculating aquaculture (where water is consistently cycled and filtered) emit ~200 – 400% more GHGs than do other fishery and aquaculture production methods because of their higher energy inputs (Clark & Tilman, 2017; Clune et al., 2017; Tilman & Clark, 2014).

The total land required to produce a unit of food follows a similar trend as GHG emissions. Plant-based foods have the lowest land use requirements per unit of food; dairy and eggs require several times more land than plant-based foods; pork and poultry require ~100 – 400% more land than dairy and eggs; and ruminant meats require ~2,000 – 10,000% more land (depending on the extent of grazing) than plant-based foods. Production of ruminant meats requires more land than other food, in part because of the inefficiency at which they convert feed into human-edible food, but also because of they are grazed on pastureland. It is unclear how much land is required to produce a unit of fish in aquaculture systems, but it is likely similar to the amount needed for eggs, poultry or pork because they have similar feed requirements and efficiencies (Tilman & Clark, 2014).

Nutrient pollution per kcal of food, measured as the amount of nutrients that leave a farming system and enter the surrounding environment, follows similar trends. Production of plant-based foods results in the smallest amount of nutrient pollution. Although production of a kcal of fresh fruits and vegetables results in about twice the amount of nutrient pollution as other plant-based foods, this is largely because the caloric contents of vegetables and fruits are low. However, most fruits and vegetables are eaten for their vitamin, mineral and antioxidant contents rather than for their calories. When measured per serving of food produced, fruits and vegetables have nutrient pollution similar to or lower than other plant-based foods. Production of dairy, eggs, poultry, and pork creates intermediate amounts of nutrient pollution, approximately ~1,000 – 5,000% higher per unit of food produced than the nutrient pollution from producing plant-based foods. Production of ruminant meat results in the largest amount of nutrient pollution per unit of food, ~10,000% higher than production of plant-based foods (Clark & Tilman, 2017). Aquaculture production in closed body of water can also contribute to nutrient pollution (FAO, 2016).

Animal-based foods often have higher environmental impacts than plant-based foods because of the inefficiency with which animals convert feed into human-edible food.

Ruminant animals (mainly cattle, sheep and goats) have an additional impact because of the methane produced in their rumen by their digestive symbionts. For non-ruminant animals, the environmental impact of animal-based foods is correlated with feed conversion ratio (FCR), or the amount of feed protein required to produce a gram of edible animal protein (Tilman & Clark, 2014). Eggs and dairy have the lowest impact of animal source foods with FCRs of 2.6 and 3.9, respectively. Poultry and pork have about twice the impact of eggs and dairy and have FCRs of 4.9 and 5.7, respectively. Ruminant meats have much higher impacts both because of their greater FCR's (mutton and goat have FCR = 14.4 and beef has FCR = 19.3) and also because of methane released by their digestive symbionts.

These LCA meta-analyses effectively illustrate the general relative environmental impacts of different foods. However, the majority of LCA publications used in these meta-analyses measured the environmental impacts of production systems that were westernized, high input, and highly mechanized (Clark & Tilman, 2017; Clune et al., 2017). In addition, because many of the environmental impacts of food production are context dependent and are in part determined by the local ecosystem, it is possible that the environmental impacts of food production in less-westernized, lower-input, and less-mechanized production systems may differ from those discussed here (Carlson et al., 2016; Herrero et al., 2013).

Foods Types, Diets and Health:

A wide variety of methods have been used to study the effects of different diets and foods on human health. Here we mainly focus on prospective cohort studies, which examine diets and health outcomes for a cohort of individuals through time. These studies statistically control for age, gender, race, socioeconomic variables, history of smoking, and other variables in determining how different foods or diets may be associated with disease outcomes. By controlling for these factors, and by tracking consumption patterns and disease outcomes through time for large numbers of individuals, researchers are able to estimate the health impact of consuming an additional serving of food per day.

These studies reveal that the health impacts of food consumption are often qualitatively similar to the environmental impact of food consumption. For instance, consuming an additional serving per day of minimally processed plant-based foods is typically beneficial to health (Afshin et al., 2014; Aune et al., 2016b, Aune et al., 2017; Aune et al., 2013b; Grosso et al., 2015; Wu et al., 2015); consuming an additional serving per day of dairy (Aune et al., 2013a; Mullie et al., 2016), eggs (Rong et al., 2013; Wallin et al., 2016), and chicken (Abete et al., 2014; Feskens et al., 2013) does not significantly impact health outcomes; and consuming an additional serving per day of red and processed red meats (Chen et al., 2013; Feskens et al., 2013; Wang et al., 2015) contributes to poor health. While consumption of both red and processed red meats contributes to poor health, consumption of processed red meats is associated with more negative health outcomes than unprocessed red meats, perhaps because of the higher levels of nitrate and nitrite in processed meats (Etemadi et al., 2017). The exceptions to the trend are that consuming an additional serving per day of fish (Daley et al., 2010; Zhao et al., 2015; Zheng et al., 2012), which often has environmental impacts similar to dairy and chicken, is beneficial to health while consuming an additional serving per day of sugar (Tasevska et al., 2014; Yang et al., 2014) or sugar-sweetened beverages (Huang et al., 2014; Imamura et al., 2015; Xi et al., 2015), both of which have relatively low environmental impacts, often contributes to increased disease risk.

Other prospective cohort studies have compared the health outcomes of individuals that have omnivorous dietary patterns to individuals that consume more plant-based diets such as a Mediterranean, pescetarian, vegetarian, or vegan diet. Mediterranean diets are characterized as containing large amounts of fruits, vegetables, whole grains, legumes, moderate amounts of seafood, small amounts of other meats, and as using olive oil as the primary oil. Vegetarian diets contain dairy and eggs, but no fish or other meat; pescetarian diets include fish, dairy, and eggs, but no other meat, and vegan diets contain no animal-based foods.

These dietary analyses have consistently found that diets higher in plant-based foods are associated with reduced disease risk compared to omnivorous dietary patterns (Figure 3b) (Tilman & Clark, 2014). For instance, increased adherence to a Mediterranean diet, for example, reduces risk of diabetes by ~7% (Schwingshackl et al., 2015), and from heart disease by ~10% (Sofi et al., 2013), and total mortality by 8% (Sofi et al., 2013) relative to westernized diets. Strict adherence to a Mediterranean diet would likely offer larger health benefits (Dinu et al., 2017). Pescetarian (Orlich et al., 2013; Tonstad et al., 2013), vegetarian (Dinu et al., 2017; Satija et al., 2016), and vegan (Dinu et al., 2017; Orlich et al., 2013; Tonstad et al., 2013) diets also provide health benefits relative to westernized dietary patterns characterized by high consumption of calories, animal products, and sugars and sweeteners.

While prospective cohort studies are useful in examining the average health impact of different foods, they have some limitations. Most analyses examined food consumption and health outcomes in primarily Caucasian populations; however, health outcomes may differ between ethnicities (Khan et al., 2011; Siegel et al., 2017) and genders (Khan et al., 2011; Mosca et al., 2011). For instance, diabetes incidence is higher in men than women in Chinese, South Asian, and white populations (Khan et al., 2011), and African Americans are more predisposed to many cancers than Hispanics, Asian Americans, and Caucasians (Siegel et al., 2017). In addition, analyses that also control for genetic disposition sometimes differ in their results. For example, prospective cohort studies have found that consuming intermediate amounts of alcohol (Ronksley et al., 2011) or coffee (Ding et al., 2014) would reduce the risk of cardiovascular disease, whereas Mendelian analyses that also control for genetic markers have found no health benefit of any amount of alcohol (Holmes et al., 2014) or coffee (Nordestgaard & Nordestgaard, 2016) consumed. Furthermore, the health benefit of consuming an additional serving of food may be non-linear. For example, consuming additional whole grain cereals when they are already consumed in quantities >100g/day offers smaller health benefits for coronary heart disease and no additional health benefits for stroke or cardiovascular disease (Aune et al., 2016b).

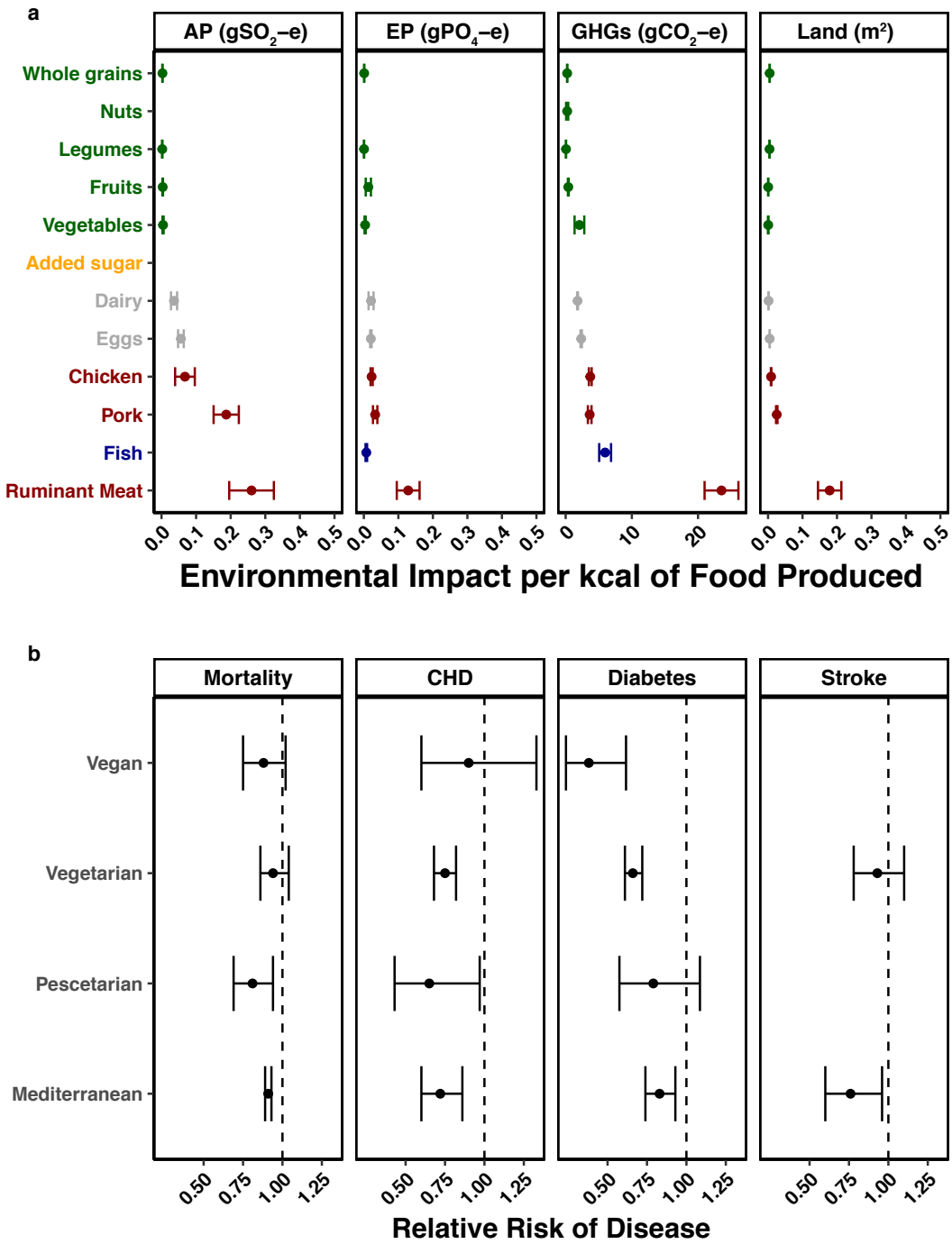

Figure 3: Environmental and health impacts of different foods or dietary patterns. **(a)** Environmental impact on a per kcal of food produced and **(b)** health outcomes of

consuming different dietary patterns. Data for a is from ref (Clark & Tilman, 2017); data for b is from refs (M Dinu et al., 2017; Dinu et al., 2017; Orlich et al., 2013; Satija et al., 2016; Tonstad et al., 2013).

Environmental and health forecasts of dietary patterns

Environment

Shifts towards diets higher in calories and animal-based foods, when combined with population growth, are expected to increase global agricultural production by 60 – 100% between 2005 and 2050. This large increase in agricultural production is forecast to drive large increases in diet-related environmental impacts such as GHG emissions, land clearing to create croplands and pastures, increased risks of species extinctions and biodiversity loss, pollution of freshwaters, aquifers, and marine ecosystems, and $PM_{2.5}$ air pollution from agricultural fertilizers and animal production (Figure 4a).

Agricultural GHG emissions come from four major sources. When land is cleared to create new pastures or croplands, the aboveground and belowground biomass that had been present on that land is commonly burned or decomposes, and the carbon in the biomass is released to the atmosphere as CO_2. Use of nitrogen fertilizers is a second major cause of agricultural GHG emissions. About 1% applied N in nitrogen fertilizers is microbially converted into the gas nitrous oxide (N_2O), which is ~300 times more potent as a GHG than CO_2 on a per mass basis. Third, production of rice and ruminants emits methane, a GHG ~25 times more potent than CO_2. Fourth, fossil fuel and electricity use on farms release GHG. In total, agricultural currently accounts for ~25 – 33% of total global GHG emissions.

Diet-related GHG emissions are projected to increase ~50 – 80% between 2010 and 2050 (Bajzelj et al., 2014; Popp et al., 2010; Springmann et al., 2016; Tilman & Clark, 2014) because of increased consumption of ruminant meats, but also because of land clearing, increased fertilizer application, increased production of rice, and a growing global population. Notably, this projected increase in agricultural GHG emissions is greater than the current global emissions from all forms of transportation combined. Thus, during a

period in which vehicle electrification has been proposed as a partial solution to climate change, any climate change benefits it may provide would be more than offset by increases in agricultural emissions if diets continue to change along current trajectories.

Forecasts of agricultural land expansion to 2050 range from ~200 – 1,000 million hectares because of differing forecasts of future increases in yields and in per capita food demand (Alexandratos & Bruinsma, 2012; Bajzelj et al., 2014; Schmitz et al., 2014; Tilman et al., 2017; Tilman et al., 2011; Tilman & Clark, 2014). The estimate that cropland will expand by ~200 million hectares assumed that crop yields would increase exponentially and that per capita food demand would increase to a lesser extent than do other analyses. There is little empirical support for exponential increases in yields; this would be inconsistent with the slowing rate of yield increases observed in most world regions during the past 30 years (Grassini et al., 2013). The estimate that cropland could expand by 1,000 million hectares extrapolated past yield trends and assumed larger increases in per capita crop demand. Other analyses forecast intermediate increases in cropland extent to 2050 ranging between 200 – 700 million additional hectares of cropland over the next several decades (Bajzelj et al., 2014; Schmitz et al., 2014; Tilman et al., 2017; Tilman & Clark, 2014).

Agricultural land expansion would increase the threats to biodiversity. Threats to biodiversity are forecast to increase the most in developing and tropical nations, where the amount of agricultural land expansion is expected to be greatest (Tilman et al., 2017; Visconti et al., 2016). Large-bodied animals will be at particular risk from agricultural land expansion because of their large habitat requirements and low population sizes and densities (Tilman et al., 2017). For instance, Visconti et al (2016), estimate that mean species population abundance of large mammals would decline by ~18 – 35% by 2050 while Tilman et al. (2017) forecast that threats to large-bodied mammals and birds will more than double by 2060, equating to a future IUCN status for large-bodied mammals and birds of greater than “endangered” in tropical regions. Threats to medium- and small-bodied organisms are also forecast to increase. These analyses, however, may

underestimate future extinction risks because they do not account for the negative impact that habitat fragmentation (Haddad et al., 2015; Laurance et al., 2002) or agricultural intensification (Storkey et al., 2011) may have on biodiversity.

Nitrogen (Bodirsky et al., 2014; Bouwman et al., 2013a; Bouwman et al., 2013b; Tilman et al., 2001; Tilman et al., 2011) and phosphorus (Bouwman et al., 2009; Bouwman et al., 2013b; Tilman et al., 2001) fertilizer applications are also forecast to increase as diets shift and populations grow. Global agricultural nitrogen use is forecast to increase by ~0 – 190% from 2010 to 2050 depending on the extent of technological adoption, international trade, and agricultural efficiency (Bodirsky et al., 2014; Bouwman et al., 2009; Bouwman et al., 2013b; Tilman et al., 2001; Tilman et al., 2011) while phosphorus use is forecast to more than double over the same time period (Bouwman et al., 2009; Tilman et al., 2001). Increased nutrient applications on agricultural land may also increase agricultural runoff, which in turn can lead to poor human health outcomes through polluted water supplies and the formation of marine dead zones where marine aquatic life cannot survive.

Diet-related environmental impacts are forecast to increase the most in developing nations because of the rapid rate expected dietary transitions towards more meat-based diets and high rates of population growth. In comparison, diet-related environmental impacts are expected to remain fairly constant in high-income and developed nations because of much lower rates of population growth and fairly stagnant dietary patterns.

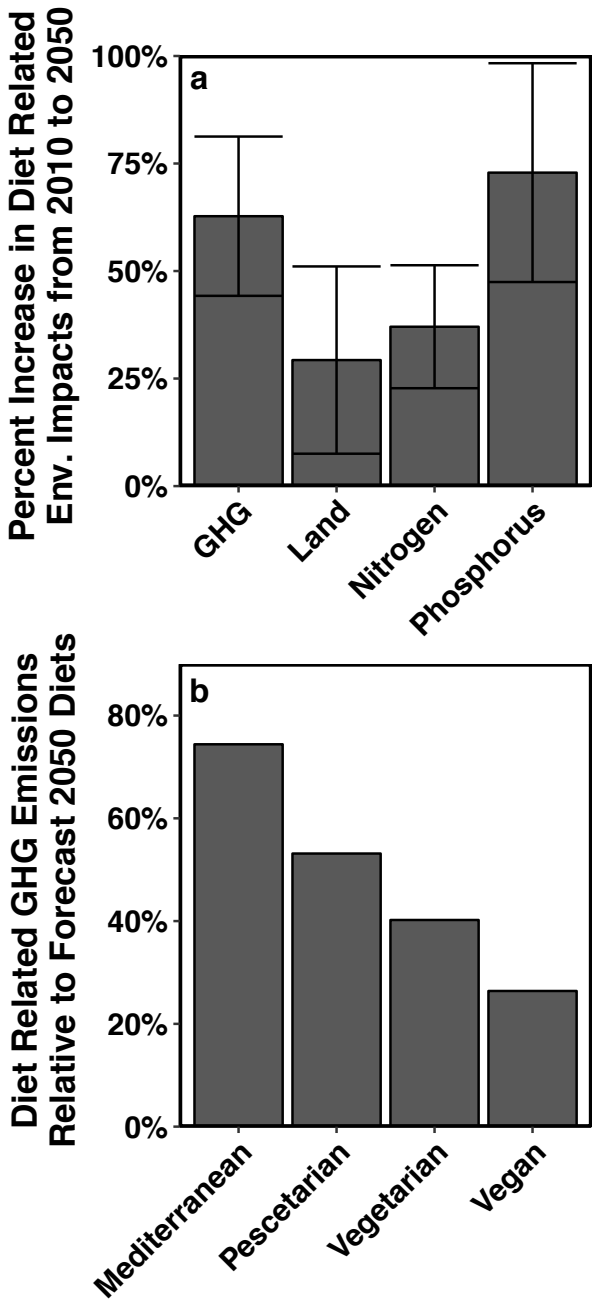

Figure 4. Environmental impact of future diets. (a) Proportional increase in diet-related environmental impacts if current dietary trajectories continue to 2050. **(b)** Environmental impacts of healthier more plant-based diets relative to expected 2050 diets, measured as a percent of expected 2050 diets if current dietary trajectories were to continue. Data is from refs (Alexandratos & Bruinsma, 2012; Bajzelj et al., 2014; Bodirsky et al., 2014; Bouwman et al., 2009; Bouwman et al., 2013b; Popp et al., 2010;

Schmitz et al., 2014; Springmann et al., 2016; Tilman et al., 2011; Tilman & Clark, 2014).

Health

Projected dietary shifts to 2050 are forecast to increase prevalence of diet-related diseases (Euromonitor International, 2018; World Health Organization, 2016). Diabetes prevalence is forecast to increase by 55% globally from 2000 to 2030. The increase in diabetes prevalence is expected to be more rapid in regions currently undergoing large shifts towards diets higher in meats, sugars, and total calories. Indeed, by 2030 diabetes prevalence is forecast to increase by ~100% in the Middle East and North Africa, increase by >70% in South and Southeast Asia and by ~60% in Sub-Saharan Africa (Euromonitor International, n.d.; World Health Organization, 2016). More affluent regions such as Europe (~22% increase) and North America (~37% increase) have smaller forecasted increases in diabetes by 2030 because of smaller dietary and lifestyle changes (Euromonitor International, 2018; World Health Organization, 2016).

Global forecasts of other diet-related mortality show similar trends. From 2005 to 2050, cardiovascular disease mortality is forecast to increase >50% in China (Moran et al., 2010) and the United States (Heidenreich et al., 2011). Prevalence of overweight and obesity will also continue to increase if dietary patterns and lifestyles do not change, with the largest increases forecasted for currently developing nations (Springmann et al., 2016). In total, diet-related diseases will account for two-thirds to three-quarters of the total global burden of disease by 2030 if current trajectories continue (Beaglehole & Bonita, 2008).

Dietary shifts as a solution to the diet-health-environment trilemma

Adopting a healthier and more plant-based diet, such as a Mediterranean, vegetarian, pescetarian, or vegan diet, could provide large global environmental benefits relative to

current and forecasted future diets (Aleksandrowicz et al., 2016). Global adoption of these healthier diets could reduce global 2050 diet-related GHG emissions by ~30 – 60% (Figure 4b; Bajzelj et al., 2014; Springmann et al., 2016; Tilman & Clark, 2014), land use by ~20 – 35% (Bajzelj et al., 2014; Tilman & Clark, 2014), decrease future threats to biodiversity (Tilman et al., 2017), and reduce nitrogen (Bodirsky et al., 2014; Bouwman et al., 2013b) and phosphorus (Bouwman et al., 2013b) fertilizer inputs relative to forecasted future dietary impacts.

The environmental benefits of adopting healthier and more plant-based diets would vary greatly among nations if one were to look solely at the changes in environmental impacts associated with a change to healthier diets. However, in an ethical context in which per capita international equitability is a central principle, the dietary emissions of healthy diets would be the baseline. Adopting healthier diets in developed nations would reduce per capita diet-related environmental impacts down to this baseline, largely because of reduced consumption of ruminant meats, other meats, and total calories. Other countries that consume large quantities of ruminant meat, such as Argentina and Brazil, would also experience large environmental benefits from healthier diets. Adoption of healthier diets in food-insecure developing nations[49] would bring their emissions up to the ethical baseline and could prevent much of the increase in diet-related disease and environmental impacts that would otherwise accompany the dietary shifts associated with eventual economic development and urbanization in these nations.

Healthy diets do not necessarily have lower environmental impacts, while diets with lower environmental impacts are not necessarily healthy. For instance, an isocaloric substitution of fruits and vegetables for meats would likely improve diet-related health outcomes but would also increase diet-related GHG emissions (Vieux et al., 2012). However, a combination of whole grains, nuts, legumes, dairy, eggs, and fresh produce are most often substituted for meats, could also increase health outcomes, and these substitutes would lower GHG emissions (Pan et al 2012). Furthermore, adopting the U.S. government recommended diet would increase diet-related GHG emissions in the U.S.

(Heller & Keoleian, 2014). In contrast, a hypothetical diet that met caloric needs and minimized diet-related greenhouse gas emissions reduced GHG emissions by 90% relative to the usual diet of the U.K., but was unhealthy, containing only seven food items in unrealistic quantities and no fruits or vegetables (Macdiarmid et al., 2012).

Shifting towards healthier dietary patterns would improve diet-related health outcomes. Increased adoption of a combination of Mediterranean, pescetarian, vegetarian, or vegan diets would reduce the risk of diabetes, cancer, heart disease, overweight and obesity, and total mortality relative to expected dietary patterns in 2050 (Springmann et al., 2016). In total, adoption of a more plant-based diet would reduce mortality from coronary heart disease, stroke, cancer, and type 2 diabetes by 12 – 19% and total global mortality by 6 – 10% (5.1 – 8.1 million fewer deaths per year) by 2050. The health benefits of such diets are primarily from reduced consumption of red meat and decreased prevalence of overweight and obesity, but also because of increased intake of nuts, fruits, vegetables (Springmann et al., 2016). Epidemiological studies examining dietary patterns and health outcomes also show that adoption of plant-based diets would improve health outcomes in affluent regions that consume large quantities of animal based foods (e.g. Key et al., 2009; Orlich et al., 2013), although increased consumption of animal-based foods in undernourished populations might improve health outcomes (Smith et al., 2013).

Other routes to improved agricultural sustainability

There are many ways other than adopting more plant-based diets to improve agricultural sustainability. The next section highlights several inefficiencies in the current agricultural system that, if overcome, could greatly increase agricultural sustainability.

Closing Yield Gaps:

Crop yields in many developing nations could be greatly increased by greater access to agricultural inputs (Global Yield Gap and Water Productivity Atlas, 2017; Mueller et al., 2012). For instance, 94 nations have average crop yields that are less half of their potential, while 43 nations have yields less than one-third of their potential (Figure 5).

Nearly half of these nations are in Sub-Saharan Africa; others are in South and Southeast Asia and Latin America. Increasing crop yields by decreasing the difference between current and potential yields, an idea as known as closing yield gaps, would simultaneously improve environmental outcomes (Bajzelj et al., 2014; Tilman et al., 2017; Tilman et al., 2011; Tilman & Clark, 2014), increase farmer income, and improve food security and diet-related health outcomes (Foley et al., 2011; Godfray et al., 2010). For instance, global food production would increase ~28% or ~58% if every nation were to achieve crop yields equivalent to 75% or 95% of their potential crop yields, respectively (Foley et al., 2011). Smaller closures in yield gaps would also have globally significant ramifications; increasing crop yields to 50% of their potential yields in low performing areas would increase crop production enough to feed an additional ~850 million people per year (West et al., 2014).

Closing yield gaps is possible with existing technologies and management techniques. Planting and intercropping agricultural fields with grains and legumes (Vandermeer, 1989), using cover crops and manure to increase soil fertility, increasing access to improved seeds, fertilizers, and pesticides, and better timing fertilizer application with crop nutrient demand are effective methods at increasing crop yields (Tilman et al., 2002). National government programs in Malawi (Dorward & Chirwa, 2011), Rwanda, Zambia, Ghana, Mali, and Senegal (Druilhe & Barreiro-hurlé, 2012) that increased access to agricultural inputs successfully increased crop yields by 20 – 80%. Smaller-scale interventions such as integrated pest management (Z. R. Khan et al., 2014) and use of nitrogen fixing crops during fallow periods, among other methods (Garrity et al., 2010; Hall et al., 2006), have also increased crop yields in low-yielding regions.

Closing yield gaps is not without potential environmental or economic drawbacks. Increasing crop yields by closing yield gaps often requires increased nutrient inputs such as water and fertilizer (Mueller et al., 2012). Increasing water use in arid and drought-stricken regions could stress water resources, and may not be possible if irrigation water is in short supply. Increasing fertilizer application could also lead to increased nutrient

runoff if management techniques designed to limit nutrient runoff, especially efficient methods of fertilization, are not also adopted when fertilizer inputs are increased. In addition, maintaining yields at levels greater than ~75 – 85% of maximum potential yields may not be more economically beneficial, dependent on crop and fertilizer prices, than maintaining yields at slightly lower levels (Lobell, Cassman, & Field, 2009).

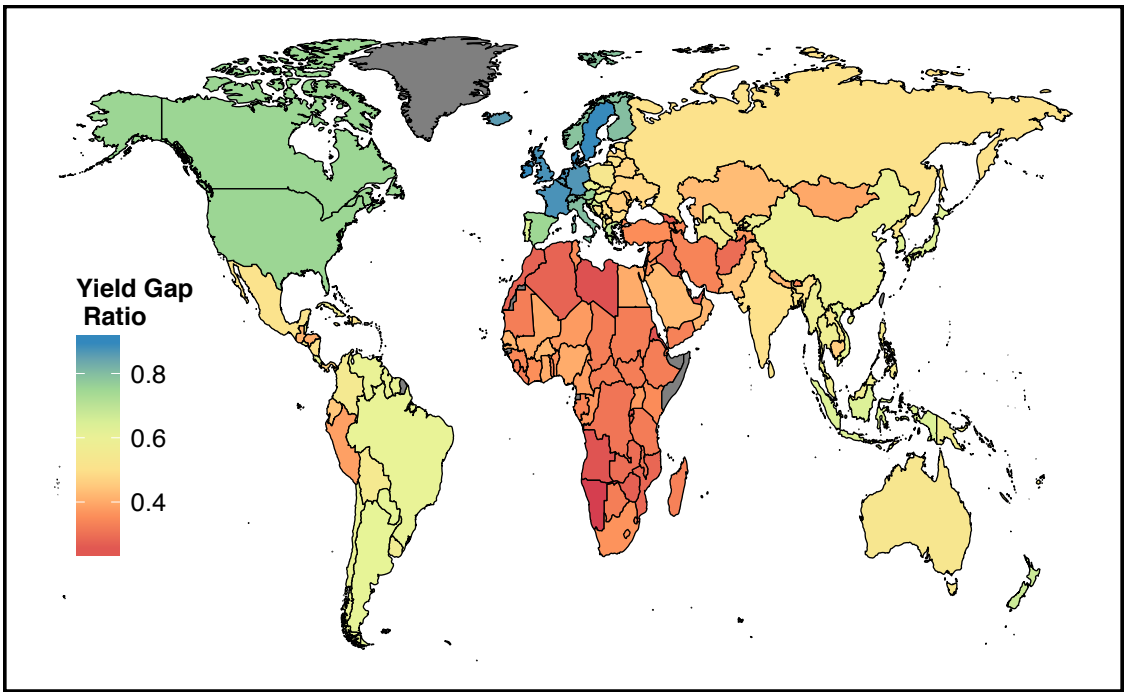

Figure 5. Existing crop yield gaps. The ratio of current yields to potential yields, based on estimates from Global Yield Gap and Water Productivity Atlas (2017) and Mueller et al., (2012). A ratio of 0.2 indicates that a nation, on average, has crop yields 1/5 of what a nation is capable of yielding. Low ratios indicate large yield gaps, or the difference between current yields and potential yields.

Reducing Food Waste

Thirty to forty percent of global food production is ultimately lost or wasted (Gustavsson et al., 2011). Lower-income and developing nations waste a larger proportion of food during production and transport, largely because of lack of infrastructure and poor storage facilities. In contrast, higher-income nations tend to waste more food at retail stores and households, partially because of aesthetic quality standards. Solutions designed to reduce food loss and waste will as such need to account for local contexts and the underlying causes of food loss and waste.

Reducing food loss and waste could improve environmental outcomes and increase food security. For instance, cutting food loss and waste in half would reduce global irrigation water use by ~11%, land use by ~9%, and fertilizer use by ~10% (Kummu et al., 2012). In addition, halving food loss and waste would also potentially increase food availability by ~1,300 trillion kcal per year by 2050, or ~22% of the estimated crop production increase required to meet estimated crop production in 2050 (Lipinski et al., 2013).

Reducing food waste is possible at all points in the food supply chain. Intermarché, a French supermarket, reduced food waste and increased their profits by selling misshapen produce at a discount. Other supermarkets have since adopted similar programs. National governments, such as those in France and Italy, have laws that encourage or require grocery stores to donate food that would otherwise be wasted. Increasing access to refrigeration, storage technologies and facilities, and market access, as well as improving crop production and harvest techniques could reduce food loss and waste in low-income nations (Gustavsson et al., 2011).

Increasing Efficiency of Fertilizer Applications

Increasing fertilizer use efficiency, or the amount of food produced per unit of fertilizer input, would reduce nutrient runoff and emissions of pollutants that contribute to climate

change and reduced air quality (Robertson & Vitousek, 2009; Vitousek et al., 2009). Low fertilizer use efficiency results from over application of fertilizer and temporal and spatial mismatch between fertilizer application and crop nutrient demand. Mismatches between fertilizer application and crop nutrient demand ultimately result in fertilizer leaching into ground waters (e.g., aquifers), flowing into surface waters (e.g., rivers), and, for nitrogen, being emitted as nitrous oxide that causes climate change or as ammonia that creates $PM_{2.5}$. Fertilizer runoff can create dead zones, cause biodiversity loss, while also contributing to poor health outcomes by increasing nitrate and nitrite levels in drinking water (Ward et al., 2005) and contributing to air pollution (Bauer et al., 2016; Lelieveld et al., 2015).

Improving fertilizer use efficiency is possible with existing technologies and management strategies. Precision agriculture, a management technique that improves the match between crop nutrient demand and nutrient application, has reduced fertilizer runoff in a variety of crops (Robertson & Vitousek, 2009). Incorporating cover crops into crop rotations can also reduce nutrient runoff, while using nitrogen-fixing crops as cover crops would simultaneously reduce the need for nitrogen fertilizer inputs. Creating buffer strips at edges of pastures (Heathwaite et al., 1998) and croplands (Borin et al., 2010; Schulte et al., 2017) can decrease fertilizer runoff by >90% and herbicide runoff by >60% while also providing ecosystem services such as carbon sequestration (Borin et al., 2010) and habitat for native pollinators (Schulte et al., 2017).

Governmental policy interventions have been effective at improving fertilizer use efficiency and reducing fertilizer runoff. The EU Nitrates Directive, established in 1991, aimed to decrease fertilizer runoff because of its effect on human health (European Community, 1991). Since the Nitrates Directive was established, N fertilizer application decreased ~30% while P and K applications decreased 70% without negatively affecting the rate at which national crop yields (measured as national mean kcal/ha) increased (FAO, 2017). In addition, water quality and human health outcomes associated with excess nutrient runoff have improved in the EU (European Commission, 2013). Analyses

conducted in other developed nations have also shown that national-average fertilizer application rates could be decreased by ~25% without negatively impacting crop yields (Vitousek et al., 2009).

Land Use Planning

Conservation-based land use planning could reduce agriculture's future environmental impacts. Establishing new "protected areas" (e.g. national parks, conservation reserves, etc) to meet and/or exceed the Aichi biodiversity targets(Convention on Biological Diversity, 2017) would improve biodiversity outcomes (Butchart et al., 2015), especially if protected areas are linked together to allow for migration between neighboring protected areas and to decrease habitat fragmentation (Packer et al., 2013). Increasing enforcement of existing protected areas to reduce hunting, poaching, and resource extraction would also improve biodiversity outcomes, but could also increase food insecurity in regions that rely on the nutrition provided by bushmeat (Cawthorn & Hoffman, 2015).

Leveraging national, regional, and global food trade patterns to avoid increased production in biologically sensitive or low-yielding regions could also improve global environmental outcomes. For example, a recent analysis showed that preferentially growing crops in countries with high yields for export to countries with low yields could prevent ~25 – 75% of the expected increase in future threats to biodiversity (Tilman et al., 2017). Such trade-based conservation measures, however, would be constrained by local food preferences and should ensure adequate food sovereignty and security. Analyses conducted at smaller spatial scales have also shown that land use planning can improve biodiversity outcomes while simultaneously increasing economic output (Polasky et al., 2008).

Integrated Agriculture

There are environmental tradeoffs between organic (as it is called in the USA; ecological in Europe) and conventional agricultural systems. On average across all crops, per unit of

food produced, organic agricultural systems require more land (Clark & Tilman, 2017; Seufert & Ramankutty, 2017; Seufert et al., 2012) and have higher rates of nutrient runoff. Conventional systems require more energy (Clark & Tilman, 2017; Seufert & Ramankutty, 2017), have lower soil organic carbon stocks (Gattinger et al., 2012), and decreased biodiversity (Bengtsson et al., 2005; Hole et al., 2005; Mäder et al., 2002) relative to organic systems. Organic foods also have lower pesticide residues (Baker et al., 2002) and higher micronutrient concentrations (Hunter et al., 2011; Palupi et al., 2012), although these differences may not provide observable health benefits (Dangour & Lock, 2010; Hunter et al., 2011). However, some organic crops, especially short-statured fruits and vegetables, have been associated with outbreaks of *E. coli* and other pathogens if unsterilized manure was a nitrogen source (Mukherjee et al., 2004).

Integrating the benefits of different systems of food production, for instance the higher yields of conventional systems, higher soil organic carbon stocks of organic systems, and reduced reliance on synthetic inputs in organic systems and systems with higher crop diversity (Davis et al., 2012; Vandermeer, 1989), might create a more sustainable integrated agricultural system than what currently exists. Moreover, because the environmental and health impacts and productivity of agriculture are context dependent (Carlson et al., 2016; Herrero et al., 2013), the most sustainable and productive systems will vary depending on local environmental, cultural, and political systems. Developing an integrated agricultural system that combines the benefits of organic and conventional systems could lead to a more sustainable agricultural future.

Pathways to healthier and more sustainable diets

Finding ways to increase adoption of healthier and more sustainable diets may be difficult. Humans evolved to prefer foods high in fats, protein, sugar, and salt (Breslin, 2013) – which are now often found in large quantities in those commercially processed foods that are associated with poor health or large environmental impacts. Meat consumption is also sign of affluence and wealth in many cultures (Smil, 2002) while multinational corporations focus on maximizing profits by marketing tasty and cheap

foods which are also often unhealthy (Ludwig & Nestle, 2008). Recent policy interventions in culturally, socially, economically, and politically diverse nations may provide insight into future policies that could be effective at improving diet-related health and environmental outcomes if more widely adopted.

Taxation of less healthy or less sustainable foods can be effective in shifting dietary patterns. Taxes on sugar-sweetened beverages such as sodas and sweetened fruit juices in Mexico (Cochero et al., 2017) and several cities in the United States (Falbe et al., 2016) have decreased consumption of taxed beverages by up to 10%. A Danish tax on foods high in saturated fats (e.g., butter and margarine) also decreased consumption of taxed foods (Jensen & Smed, 2013). Taxes on unhealthy foods are not universally effective, nor may they be long lasting. For instance, a tax on sugar-sweetened beverages in Chicago (Dewey, 2017) was repealed after two months, while the Danish tax on foods high in saturated fats (Vallgårda et al., 2015) was repealed after two years because of consumer and political opposition.

Food labeling can be, but is not always, effective at shifting dietary habits. Back-of-package nutrition labeling increases consumption of healthier foods and decreases caloric consumption among label users (Ollberding et al., 2010). Labeling foods with "traffic light labels" (where "good" foods are labeled with green and "bad" foods labeled with red) for health (Sonnenberg et al., 2013; Thorndike et al., 2014) or environmental (Vanclay etl al., 2011) purposes has been associated with increased purchases of healthy or sustainable foods and decreased purchases of less healthy and less sustainable foods. Labeling appears to be more effective among individuals who are concerned about health or environmental outcomes (Sonnenberg et al., 2013) while the potential benefits of labeling may be negated when healthy or sustainable foods are more expensive than alternatives (Vanclay et al., 2011). Calorie labeling at fast food restaurants in the United States was enacted to reduce the number of calories purchased, although this has not been associated with a change in the number of calories purchased at fast food outlets (Swartz, Braxton, & Viera, 2011).

It seems plausible, but is as yet unclear, that integrating sustainability into government recommended dietary guidelines will increase rates of adoption of healthier diets and be effective at reducing diet-related environmental impacts. Brazil, Germany, Sweden, and Qatar have incorporated environmental sustainability into their government dietary guidelines, while the Netherlands and the United Kingdom are beginning to do so (Fischer & Garnett, 2016).

Conclusions

The diet-health-environment trilemma is created by the dietary choices people commonly make as incomes and urbanization increase, and the negative impacts of these diets on health and the environment. These negative impacts will grow greatly in the next several decades if current diet trajectories continue. For instance, by 2050, diet-related GHG emissions are forecast to increase 50-80% (Springmann et al., 2016; Tilman & Clark, 2014) and land use by 200 – 1,000 (Alexandratos & Bruinsma, 2012; Tilman et al., 2011) million hectares, while also increasing threats to biodiversity (Tilman et al., 2017; Visconti et al., 2016) and harming ecosystems and human health from excess nitrogen and phosphorus fertilizer applications and runoff (Bodirsky et al., 2014; Bouwman et al., 2009; Tilman et al., 2002). These dietary shifts would simultaneously increase the prevalence of diet-related diseases such as diabetes, heart disease, and overweight and obesity (Springmann et al., 2016), ultimately leading to diet-related diseases being three-quarters of the global burden of disease by 2030 (Beaglehole & Bonita, 2008). Global adoption of healthy plant-biased diets could prevent much of the expected increase in diet-related environmental impacts while also reducing expected diet-related mortality by 12 – 19% by 2050 (Springmann et al., 2016). Improving other aspects of the global agricultural system, such as increasing crop yields in under-yielding areas (Tilman et al., 2017; Tilman & Clark, 2014), reducing food waste (Kummu et al., 2012), improving fertilizer use efficiency (Robertson & Vitousek, 2009; Vitousek et al., 2009), and creating an integrated agricultural system that combines the benefits of organic and conventional

agricultural systems (Clark & Tilman, 2017), would further improve agricultural sustainability and food security.

Solving the diet-health-environment trilemma will not be easy. Policies designed to decrease consumption of less healthy and less sustainable foods and instead increase adoption of healthier and more sustainable foods could improve the health and environmental outcomes of dietary patterns. Existing policies such as taxing (Cochero et al., 2017; Jensen & Smed, 2013) or labeling (Sonnenberg et al., 2013; Thorndike et al., 2014) unhealthy or unsustainable foods may offer more benefits if adopted more widely (Springmann et al., 2016). However, policies also need to account for the cultural, economic, social, and political environment in order to be effective, and it is possible that a policy that is effective in one region may be ineffective in another (e.g. Cochero et al., 2017) and (Dewey, 2017)). One of the great challenges of our era is finding ways to widely achieve adoption of diets that improve the linked health and environmental outcomes.

Chapter 2: Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice

Abstract:

Global agricultural feeds over 7 billion people, but is also a leading cause of environmental degradation. Understanding how alternative agricultural production systems, agricultural input efficiency, and diets drive environmental degradation is necessary for reducing agriculture's environmental impacts. A meta-analysis of life cycle assessments that includes 742 agricultural systems and 90 unique foods produced primarily in high-input systems shows that, per unit of food, organic systems require more land and cause more eutrophication, use less energy, but emit similar greenhouse gas emissions (GHGs) compared to conventional systems; that grass-fed beef requires more land and emits similar GHG emissions compared to grain-feed beef; and that low-input aquaculture and non-trawling fisheries have much lower GHG emissions than trawling fisheries. In addition, our analyses show that increasing agricultural input efficiency (the amount of food produced per input of fertilizer or feed) would have environmental benefits for both crop and livestock systems. Further, for all environmental indicators and nutritional units examined, plant-based foods have the lowest environmental impacts; eggs, dairy, pork, poultry, non-trawling fisheries, and non-recirculating aquaculture have intermediate impacts; and ruminant meat has impacts ~100 times those of plant-based foods. Our analyses show that dietary shifts towards low-impact foods and increases in agricultural input use efficiency would offer larger environmental benefits than would switches from conventional agricultural systems to alternatives such as organic agriculture or grass-fed beef.

Introduction:

Global agriculture feeds over 7 billion people, but is also a major cause of multiple types of environmental degradation. Agricultural activities emit 25 - 33% of greenhouse gases (Edenhofer et al., 2014; Steinfeld et al., 2006; Tubiello et al., 2014); occupy 40% of Earth's land surface (FAO, 2017); account for >70% of freshwater withdrawals (Molden,

2007), drive deforestation and habitat fragmentation (Ramankutty & Foley, 1999) and resultant biodiversity loss (IUCN, 2017); and eutrophy and acidify natural aquatic and terrestrial ecosystems with agrochemicals (Vitousek et al., 1997). These impacts are likely to increase globally over the next several decades because of increases in population growth and income-dependent dietary shifts towards more meat-based diets (Bajzelj et al., 2014; Springmann et al., 2016; Tilman et al., 2011; Tilman & Clark, 2014).

We need to understand the linkages between diets, agricultural production practices, and environmental degradation if we are to reduce agriculture's environmental impacts while providing a secure food supply for a growing global population. To quantify these processes and linkages, we review and synthesize published information from 742 food production systems of over 90 foods from 164 published life cycle assessments (LCAs). LCAs are an internationally recognized way to account the inputs, outputs, and environmental impacts of a food production system. Using our meta-analysis of LCAs, we examine the comparative environmental impacts of different food production systems, different agricultural input efficiencies, and different foods.

Food production systems such as organic agriculture and grass-fed beef have been proposed as potential ways to reduce agriculture's environmental impacts (Ponisio et al., 2014). Organic agriculture, for example, is often promoted as having lower environmental impacts relative to high-input conventional systems because it replaces agrochemical inputs with natural inputs such as manure or with ecosystem services such as pest control (Azadi et al., 2011). Recent analyses examining the comparative impacts of organic and conventional systems have, of necessity, been limited to a few environmental indicators or in statistical strength of their inferences because of small sample size (Mondelaers et al., 2009; Ponisio et al., 2014; Seufert et al., 2012; Tuomisto et al., 2012). Recent increases in the number of published LCAs enables more complete analysis of the comparative impacts of organic and conventional systems across a range of environmental indicators and foods. In addition, we combine *de novo* analyses to determine the comparative environmental impacts of three other sets of production

systems: grass-fed and grain-fed beef; trawling and non-trawling fisheries; and greenhouse grown and open-field produce.

Increases in agricultural input efficiency, or the amount of food produced per unit of fertilizer or feed input, may also reduce agriculture's environmental impact (Robertson & Swinton, 2005). Agricultural systems depend on fertilizer and feed inputs to obtain and/or maintain high productivity. However, excessive application of these inputs increases agriculture's environmental impact without increasing yields or farmer profits (Vitousek et al., 2009). Our analyses examine the extent to which increases in agricultural input efficiency could reduce the environmental impact of producing a given type of food.

Previous analyses have shown that foods can differ greatly in their environmental impact (Clune et al., 2017). However, these have been limited to animal-based foods (de Vries & de Boer, 2010; Nijdam et al., 2012) or to a single environmental indicator (Clune et al., 2017; Mekonnen & Hoekstra, 2010). It is thus currently unclear how foods differ in their impacts across a range of environmental indicators, and whether foods with low impacts for one environmental indicator have similarly low impacts for other environmental indicators. Our meta-analysis enables us to make these comparisons for five environmental indicators: greenhouse gas emissions (GHGs), land use, fossil fuel energy use, eutrophication potential, and acidification potential.

The analyses and results presented here expand on current knowledge of how food production system, agricultural input efficiency, and food choice affect agriculture's environmental impacts. The results could be used to create a more sustainable agricultural future by identifying foods and food production systems that are lower-impact.

Methods:

Publication Selection and Issues Covered:

We searched Web of Knowledge, PubMed, AGRICOLA, and Google Scholar for food LCAs published before July 2015. We excluded several publications because a lack of defined system boundaries made direct comparisons with other LCAs impossible. In

addition, some LCAs conducted by for-profit companies were excluded because of potential biases. In total, we used 164 publications that analyzed 742 unique food production systems a (**Supplementary Table 1)**. We used five different environmental indicators in our analyses. These indicators are greenhouse gas emissions, land use, energy use, acidification potential (a measure of nutrient loading), and eutrophication potential (a measure of nutrient runoff) to give a broad overview of the environmental impacts of food production. The data for other environmental indicators, such as biodiversity impacts, were not present in adequate amounts to include in our analyses.

Our analyses include all relevant pre-farm and on-farm activities (fertilizer production and application, seed production, farm energy use, feed and fodder production, manure production (when used for fertilizer), manure management, infrastructure construction, etc.) and their associated environmental impacts up until a food leaves the farm. Our analyses are thus of "cradle-to-farm gate" activities; a paucity of data on post-farm gate impacts limited our ability to analyze them in a balanced manner, although a previous analysis showed that the vast majority of a food's greenhouse gas emissions stem from "cradle-to-farm gate" activities (Weber and Matthews 2008). In-depth examples of the activities included in "cradle-to-farm gate" system boundary can be found in Pelletier (2008), Hokazono and Hayashi (2012), and Torrellas et al (2012).

The majority of LCA publications included in these analyses are from agricultural systems in Europe, North America, and Australia and New Zealand (86% of systems are from these regions). Systems from China (2%), Japan (2%), the rest of Asia (5%), South America (4%), and Africa (.4%) are much less common. The results presented here are therefore indicative of highly industrialized systems and should be interpreted with this in mind. However, because the majority of systems analyzed here are highly industrialized systems, comparisons across publications will be more indicative of environmental differences between foods than if production systems were highly variable.

We found sufficient data to compare the environmental impacts of four sets of alternative production systems: organic versus conventional systems; grass-fed versus grain-fed

beef; trawling versus non-trawling fisheries; and greenhouse-grown versus open-field produce. We were also able to examine how agricultural input efficiency, or the amount of food produced per unit of agricultural input, affects a food's environmental impact, as well as how foods differ in their environmental impacts across the five environmental indicators examined.

Description of Environmental Indicators:

Five environmental indicators were used in this analysis: greenhouse gas emissions, land use, energy use, acidification potential, and eutrophication potential. The analyses were limited to these indicators because a very limited number of publications reported data for other indicators such as human health, ecotoxicity, or biodiversity. An explanation of each of the indicators included in the analyses can be found below.

Greenhouse gas emissions (GHGs) are reported in carbon dioxide equivalents, and include the greenhouse gas emissions from carbon dioxide, methane, and nitrous oxide. GHGs from activities including, but not limited to, fertilizer production and application, manure management, enteric fermentation, and are included in the results presented here.

Energy use is reported in kilojoules and includes the energy used during pre-farm and on-farm activities including, but not limited to, fertilizer production, infrastructure construction and machinery use.

Land use is a measurement of how much land is occupied during food production. It accounts for land used to grow crops and/or livestock feed, to house animals, and to pasture ruminants.

Acidification potential is reported in SO_2 equivalents and includes acidification potential from sulfur dioxide, nitrogen oxides, nitrous oxide, and ammonia, among others. Acidification potential is a measurement of the potential increase in acidity of an ecosystem. Excess acidification makes it more difficult for plants to assimilate nutrients, and thus results in decreased plant growth. Activities such as fertilizer application, fuel combustion, and manure management are included in the results presented here.

Eutrophication potential (a measure of nutrification) is reported in PO_4 equivalents and includes eutrophication potential from phosphate, nitrogen oxides, ammonia, and ammonium, among others. Eutrophication is a measurement of the increase in nutrients entering an ecosystem. Eutrophication has substantial environmental impacts including but not limited algal blooms and aquatic dead zones.

Alternative production systems:

To control for environmental and agronomic differences between publications, as well as differences in nutrient contents between foods, we compared alternative production systems by food item within publication. We first calculated the ratio of impacts of different production systems by food item within each publication, and then calculated the response ratio by taking the log of the ratio of impacts (Hedges et al., 1999). We then aggregated foods into groups of similar food types (cereals; fruits; vegetables; pulses, nuts and oil crops; dairy and eggs; and meats) to improve the power of statistical tests. We tested for significant differences between alternative production systems using t-tests on the response ratio.

Agricultural Input Efficiency:

In determining how agricultural input efficiency, or the amount of food produced per unit of agricultural input, affects a food's environmental impact, we performed regressions between a food's environmental impact and its nutrient use efficiency in crop systems or its feed use efficiency in livestock systems. We limited analyses to non-rice cereal crops and non-ruminant livestock because flooding in rice paddies and digestive processes in ruminants do not make them directly comparable with other crop and livestock systems. There is not adequate data to perform similar analyses limited to ruminant systems: comparisons would be severely limited for beef (n ~5 for GHGs and <5 for all other indicators), and only three studies provide feed use efficiency in dairy systems. For the analysis on nutrient use efficiency, we excluded crop systems that applied manure because the variable nitrogen content of manure made it impossible to calculate nitrogen inputs in these systems. In total, we examined the agricultural input efficiency of 49 non-rice cereal production systems and 53 non-ruminant livestock production systems.

Different Foods:

LCAs commonly report a food's environmental impact on a per mass basis (e.g. impacts per kg of food). However, because the nutritional values of foods come from their calories, protein, and/or micronutrients, and not from mass per se, we also calculated a food's environmental impacts per kilocalorie, gram protein, and USDA serving (Agriculture, n.d.). To compare differences between broad types of foods, we aggregated foods into 13 food groups composed of similar foods (**Supplementary Table 2**).

Results and Discussion:

Environmental Impacts of Alternative Food Production Systems

1. Organic versus conventional agriculture

Organic agriculture is a fast-growing sector in many western nations, perhaps because it is perceived as being more sustainable or healthier than conventional agricultural systems (Rigby & Cáceres, 2001). Our analyses based on 46-paired organic – conventional systems examine the comparative environmental impacts of these agricultural systems across five environmental indicators and a broad range of foods. We found that organic systems require 25 – 110% more land use ($p < 0.001$; $n = 37$), use 15% less energy ($p = .0452$; $n = 33$), and have 37% higher eutrophication potential ($p = .0383$; $n = 20$) than conventional systems per unit of food. In addition, organic and conventional systems did not significantly differ in their greenhouse gas emissions ($p = .5923$; $n = 44$) or acidification potential ($p = .299$; $n = 26$), although these were 4% lower and 13% higher in organic systems, respectively (Figure 1).

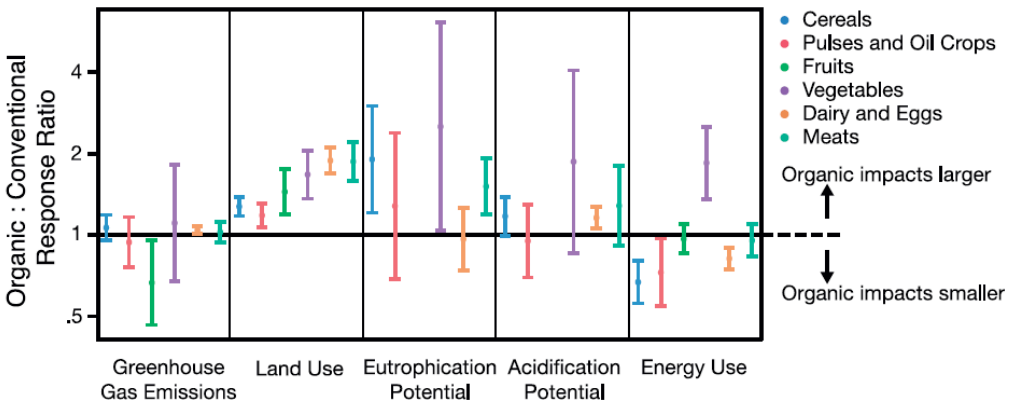

Figure 1. Response ratio of the environmental impacts of organic and conventional food production systems. Comparisons were made within publication to control for agronomic and environmental differences between publications. Plotted on a log base 2 scale, where a ratio greater than one indicates organic systems have higher impacts; a ratio less than one indicates organic systems have lower impacts. Bars are means and standard errors.

The differences in environmental impacts between organic and conventional systems are primarily driven by differences in nutrient management techniques. Organic agriculture is largely dependent on manure as a nitrogen input in contrast to conventional agriculture's use of synthetic fertilizers. Application of manure, which releases nutrients in response to environmental conditions and not crop nutrient demand (Seufert et al., 2012), often results in temporal mismatches between nutrient availability and nutrient demand and thereby increases the proportion of nutrients that are not assimilated by plants (Cassman & Walters, 2002). These temporal mismatches in organic systems result in reduced crop growth and yields and thus in increased land use. In addition, nutrient applications not incorporated into plant growth cause eutrophication and acidification, thereby driving the higher eutrophication potential and tendency for higher acidification potential in organic systems. In contrast, energy use is lower in organic systems because of organic's reduced reliance on energy-intensive synthetic fertilizer and pesticide inputs. GHG emissions are similar in organic and conventional systems because of the trade-off between application of synthetic fertilizer in conventional systems and use of manure in organic systems. Indeed, while production of conventional fertilizer is energy- and GHG-intensive, mismatches between nutrient availability and demand in organic systems dependent on manure increase the portion of reactive nitrogen in organic systems that turns into nitrous oxide, a potent greenhouse gas (Myhre et al., 2013), causing organic and conventional systems to have similar GHG emissions. Because we limited comparisons to within publication, the results presented here are therefore indicative of comparative environmental differences of organic and conventional systems at a local scale. It is possible that the comparative environmental impacts of organic and conventional systems

might differ at a regional, national, or global scale (Bengtsson et al., 2005; Phalan et al., 2011).

Previous analyses have shown that increasing nutrient application and adopting techniques such as rotational farming, cover cropping, multi-cropping, and polyculture in organic systems can halve the land use difference between organic and conventional systems (Ponisio et al., 2014; Seufert et al., 2012). Additionally, while the overall pattern is for higher land use in organic systems, organic systems have similar land use for legumes and perennial crops while the land use difference between organic and conventional systems is smaller in rain-fed systems and in systems with weakly-acidic to weakly-alkaline soils (Pimentel et al., 2005; Seufert et al., 2012).

Organic systems might offer health and environmental benefits we could not investigate with our data set. Organic foods have higher micronutrient concentrations (Hunter et al., 2011; Palupi et al., 2012) and lower pesticide residues (Baker et al 2002) than conventional foods, although these differences may not translate into improved human health outcomes (Dangour & Lock, 2010; Hunter et al., 2011). On-farm and near-farm biodiversity (Bengtsson et al., 2005; Hole et al., 2005; Mäder et al., 2002) tends to be higher in organic agricultural systems, probably because of its lower fertilizer, herbicide and pesticide inputs. In addition, soil organic carbon is higher in organic systems (Gattinger et al., 2012) because manure application promotes carbon storage in agricultural soils. However, organic agriculture would likely have a net negative impact on biodiversity and soil organic carbon at larger spatial scales because of the greater land clearing required under organic agriculture and because biodiversity (Balmord & Scharlemann, 2005; Ben Phalan et al., 2011) and carbon stocks (Gilroy et al., 2014) decrease dramatically with conversion from natural habitats.

Although organic systems have higher land use and eutrophication potential and tend to have higher acidification potential, this should not be taken as an indication that conventional systems are more sustainable than organic systems. Conventional practices

require more energy use and are reliant on high nutrient, herbicide, and pesticide inputs that can have negative impacts on human health (Mostafalou & Abdollahi, 2013; Schwarzenbach et al., 2010; Townsend, 2003) and the environment (Foley et al., 2011; Vitousek et al., 2009). Developing production systems that integrate the benefits of conventional, organic, and other agricultural systems is necessary for creating a more sustainable agricultural future.

2. Grass-fed versus grain-fed beef:

We quantitatively analyzed the environmental differences between grass-fed and grain-fed beef using 7 paired grass- and grain-fed systems. We define grass-fed systems as those where beef is raised solely on pasture or seasonally on pasture and supplemented diets of grass, silage, and fodder while overwintering. We found that grass-fed beef had higher land use requirements than grain-fed beef ($p = .0381$, $n = 4$), and tended to have higher impacts on GHGs and eutrophication (Figure 2). However, these relationships were not significant for GHGs or eutrophication, possibly because of small sample sizes (e.g. $n = 7$ for GHGs).

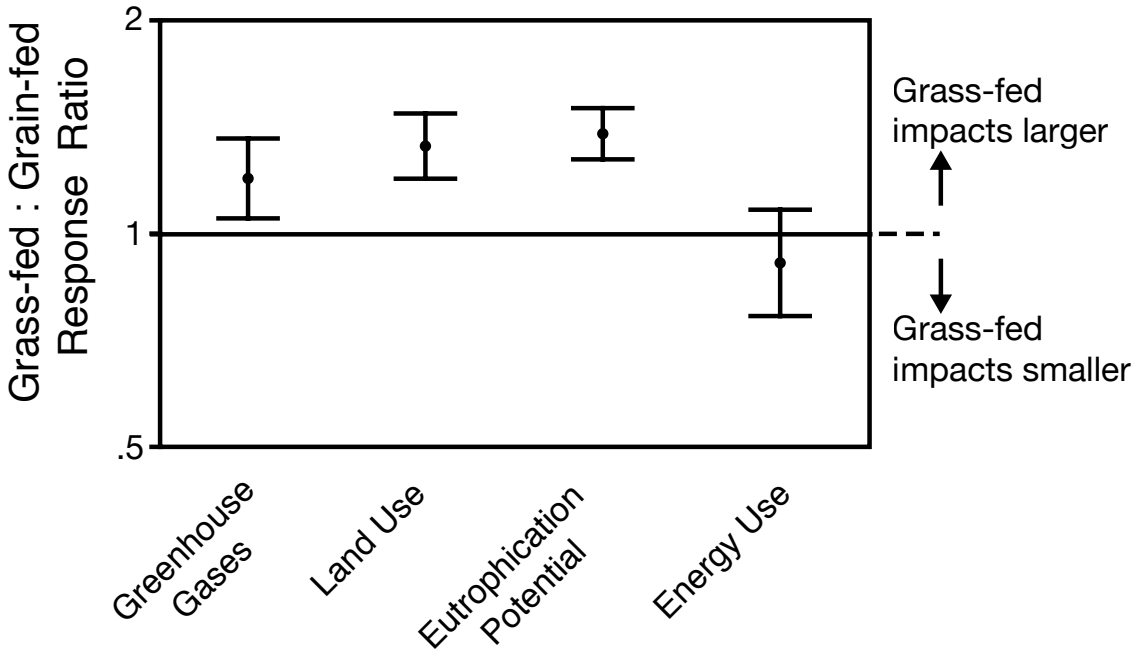

Figure 2. Response ratio of the environmental impact of grass-fed and grain-fed beef. Comparisons were made within publication to control for agronomic and environmental differences between study locations. Bars are means and standard errors. A ratio greater than one indicates grass-fed beef has higher impacts; a ratio less than one indicates grass-fed beef has lower impacts.

The higher land use and tendency for higher GHG emissions in grass-fed beef stem from the lower macronutrient densities and digestibility of feeds used in grass-fed systems (Feedipedia 2016) because they cause grass-fed beef to require higher feed inputs per unit of beef produced than grain-fed systems. Furthermore, the nutritional yields (e.g. kcal/ha) of grass, silage, and fodder are often lower, perhaps because of the cropland on which they are grown, than those of crops used for feed in grain-fed systems (e.g. maize, soy, etc). The combination of higher feed inputs and lower nutritional crop yields for feeds drive the higher land use observed in grass-fed systems. Additionally, because grass-fed cattle grow slower and are slaughtered 6 – 12 months older than grain-fed cattle, lifetime methane emissions, and thus GHGs per unit of food, tend to be higher for grass-fed beef. The source of GHGs in grass-fed and grain-fed systems further supports this explanation. Indeed, 30% and 52% of GHGs in grain-fed systems result from feed production and enteric fermentation, respectively. In contrast, feed production and enteric are responsible for 20% and 61% of GHGs, respectively, in grass-fed systems.

Grass-fed beef may have environmental and human health benefits we could not analyze with our data. For example, grass-fed systems promote soil carbon sequestration (Derner & Schuman, 2007) and within-pasture nutrient cycling while simultaneously decreasing eutrophication (Smith et al., 2013). Additionally, grass-fed beef has higher micronutrient concentrations and a fatty acid profile that might lead to improved human health outcomes relative to consumption of grain-fed beef (Daley et al., 2010). Furthermore, grass-fed beef may promote food security in cropland-scarce regions because it can be grown on land not suitable for crop production (Smith et al., 2013).

3. Trawling versus non-trawling fisheries versus aquaculture:

We classified commercial fisheries into trawling fisheries – where nets are physically dragged across a seabed – and non-trawling fisheries (midwater trawl, short and long-line fishing, and seine nets). Our analyses of 10 paired systems of trawling and non-trawling fisheries show that trawling fisheries emit 2.8 times more GHGs than non-trawling fisheries ($p = .004$; $n = 10$) (Figure 3) because of the high fuel requirements of dragging a net across a seabed. Response ratios differ greatly between fish, with non-schooling fish (flat fish) having comparatively higher impacts under trawl fisheries than do fish that form schools (mackerel, cod). Previous analyses have also shown that trawl fisheries negatively impact non-targeted species through high bycatch rates relative to other fish capture methods and through ecosystem degradation from dragging a net across a seabed (Dayton et al., 1995). Shifting from trawling to non-trawling fisheries would thus simultaneously decrease GHGs, bycatch rates, and ecosystem degradation.

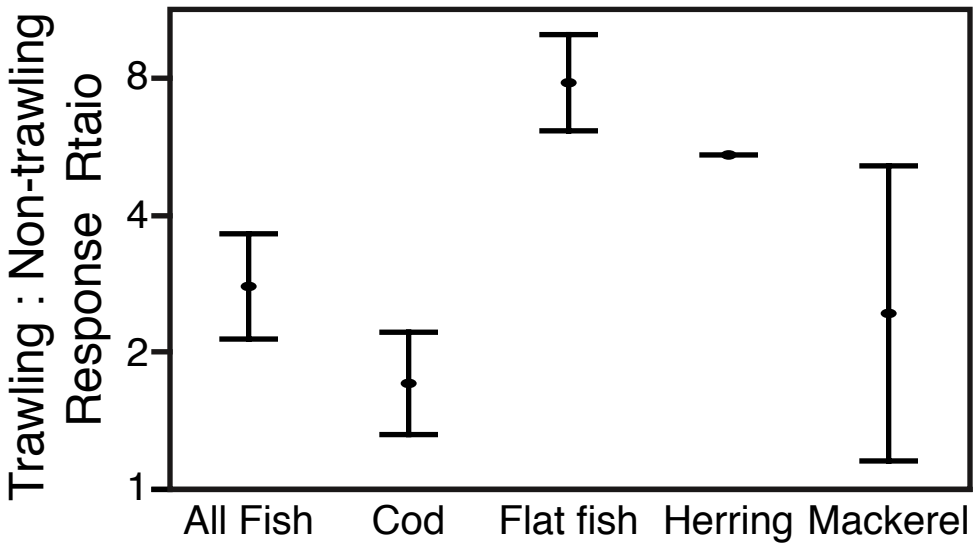

Figure 3. Response ratio of the greenhouse gas emissions of trawling and non-trawling fisheries (e.g. line, purse and seine net). Bars are means and standard errors. A ratio greater than one indicates trawling fisheries have higher greenhouse gas emissions than non-trawling fisheries.

Aquaculture, which accounts for ~45% of global fish production, could be a sustainable alternative to wild-caught fisheries (FAO, 2016). Our examination of 142 fishery and aquaculture systems indicates that, on average, non-recirculating aquaculture (e.g., aquaculture in ponds, fjords, rivers, etc.) and non-trawling fisheries emitted similar GHGs per unit of food and had emissions similar to pork, poultry, and dairy (Figures 4 and S1). In contrast, trawling fisheries and recirculating aquaculture (in tanks and other systems in which pumps and filters are used) emitted several times more GHGs than non-trawling fisheries and non-recirculating aquaculture because of their high energy requirements (Figure 4). Aquaculture-raised fish from non-recirculating systems could thus be a lower-emission alternative to trawling fisheries, an equal-emission alternative to non-trawling fisheries, and could alleviate pressure on over-harvested fisheries (Costello et al., 2012).

There can be marked differences in environmental impacts even among the lower-impact non-recirculating aquaculture systems. For instance, aquaculture at high fish densities can eutrophy closed bodies of water and cause gene exchange between farmed and wild fish varieties (FAO, 2016). In addition, shrimp aquaculture systems that require deforestation of mangroves have high environmental impacts while integrated rice-catfish agriculture aquaculture systems have comparatively low impacts (Folke & Kautsky, 1992; Páez-Osuna, 2001).

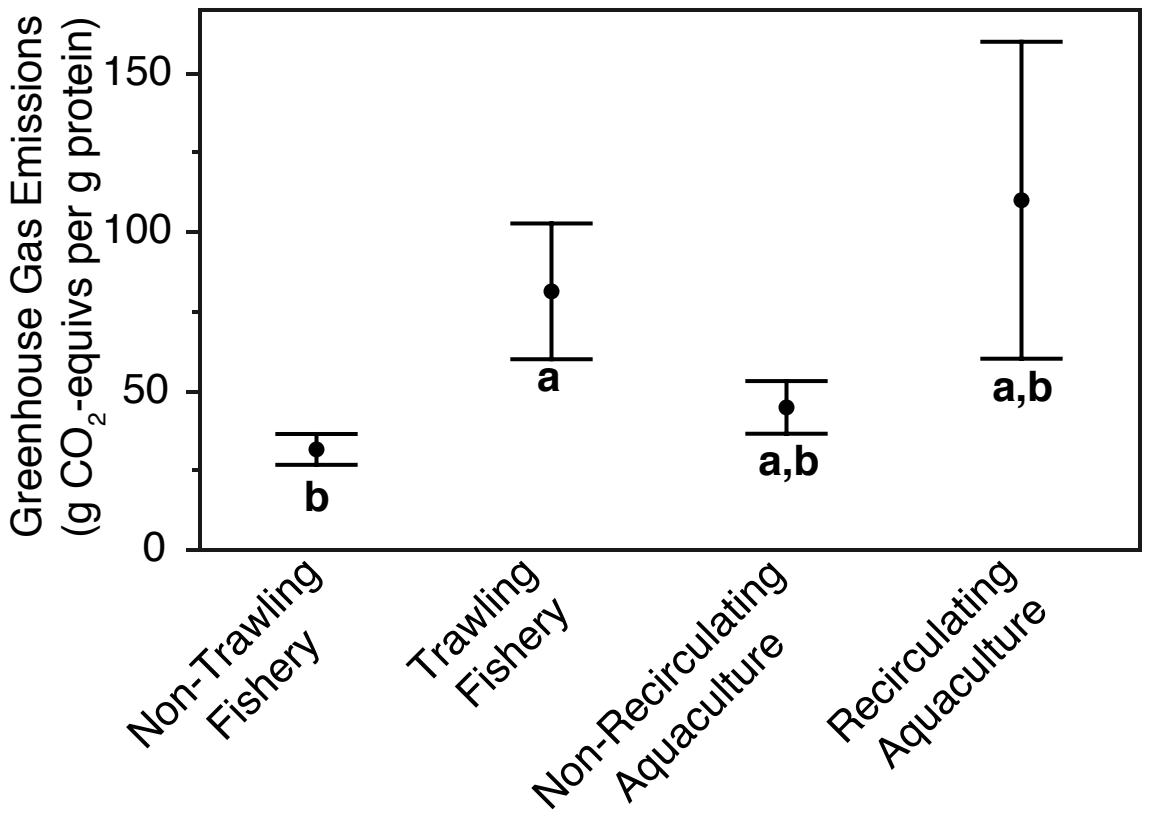

Figure 4. Greenhouse gas emissions from non-trawling (e.g. line, purse and seine net) and trawling fisheries, and from non-recirculating (e.g. pond, bag, flow-through) and recirculating aquaculture systems per gram protein. Significant differences are denoted by letters and were calculated using a Tukey's Post-hoc test.

4. Greenhouse grown versus open-field produce:

Greenhouse systems allow crops to be grown in climates and regions not suitable for crop production. Our analysis of 5 paired greenhouse – open-field systems shows that greenhouse production systems tend to emit almost three times more GHGs (Figure 5; p = .089) because of the energy required to maintain greenhouses at ideal growing conditions. While our analyses show that, on average, greenhouse production systems tend to have higher energy use than open-field systems, it is important to note that energy requirements and thus greenhouse gas emissions can differ greatly between greenhouses. For example, greenhouses that are both heated and lighted will require substantially more

energy to maintain than will greenhouses that are neither heated nor lighted. Land use in greenhouse systems was, on average, one quarter of that in open fields, but this difference was also not significant (p = .166; n = 3). Crop yields are higher, and thus land use lower, in greenhouse systems because they are maintained at ideal conditions for plant growth. The limited sample size of these analyses prevents concrete conclusions from being drawn. Future analyses examining the environmental differences between greenhouse and open-field production systems are needed to fully elucidate their comparative environmental impacts.

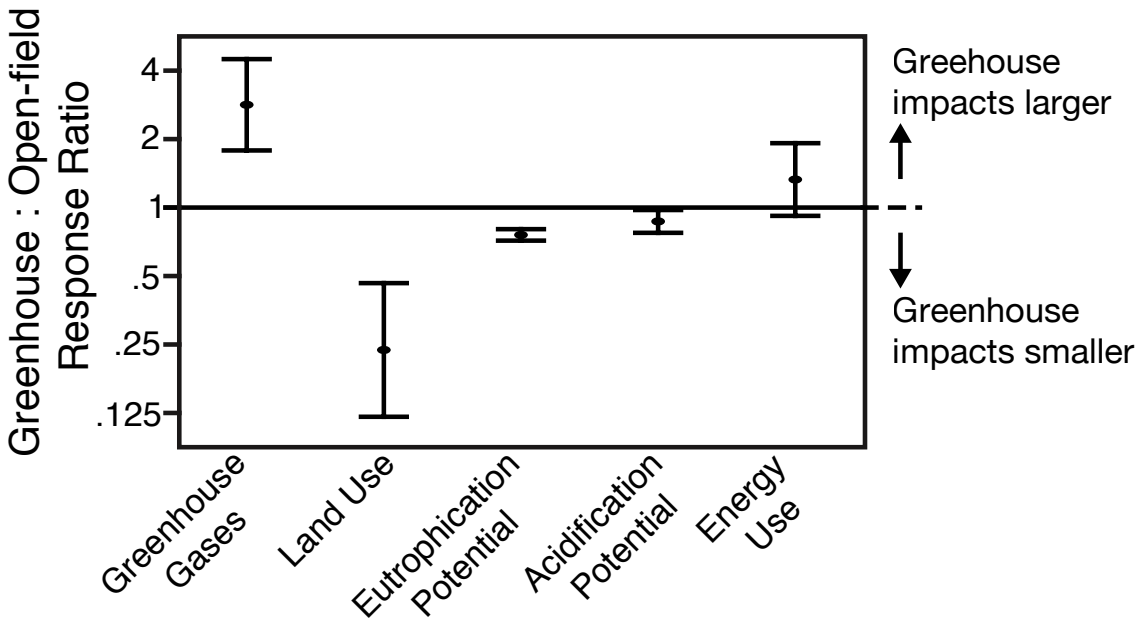

Figure 5. Response ratio of environmental impacts of greenhouse grown and open field produce. Comparisons were made within publication to control for agronomic and environmental differences between study locations. Bars are means and standard errors. A ratio greater than one indicates greenhouse systems have higher impacts; a ratio less than one indicates greenhouse systems have lower impacts.

Environmental Impacts of Agricultural Input Efficiency:

We found large differences among studies in the environmental impacts of producing the same food (Supplemental Figure 1). To examine why foods may vary in their

environmental impacts, we analyzed agricultural input efficiency, or the amount of food produced per unit of fertilizer or feed input, in 49 non-rice cereal production systems and 53 non-ruminant livestock systems. We found that higher agricultural input efficiency is consistently associated with lower environmental impacts for both non-rice cereal systems (Figure 6) and non-ruminant livestock systems (Figure 7). While the fits shown in Figures 6 and 7 are across all food items, fits for individual food by environmental indicator are almost always downward sloping and significant. Increasing agricultural input efficiency reduces a food's environmental impact because of the environmental impacts of producing agricultural inputs such as fertilizer, pesticides, and livestock feeds. However, the environmental benefits of increasing agricultural input efficiency would not be equally felt across all systems, with improvements in agricultural input efficiency having the largest environmental benefit in the least efficient systems. Further, improving efficiency in more efficient systems may only be possible at an economic cost. Emphasis should therefore be placed on improving efficiency in less efficient systems, although efficiency improvements in more efficient systems would still have environmental benefits.

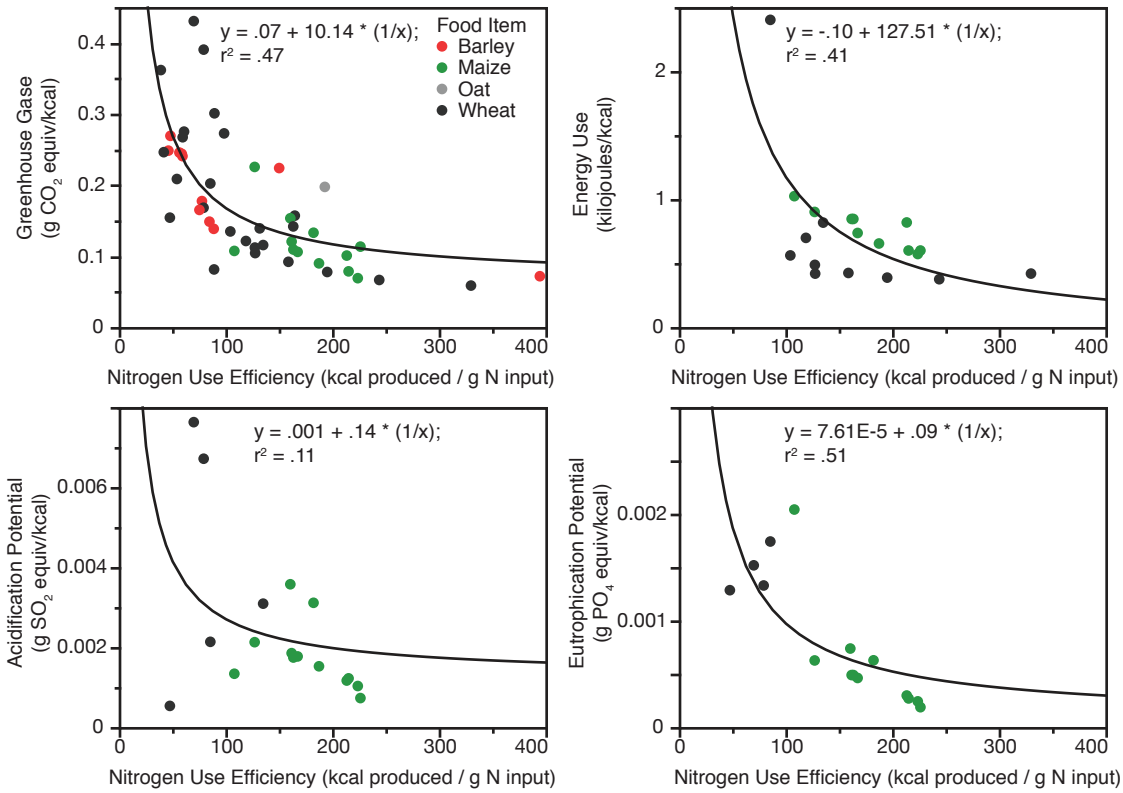

Figure 6. Correlations between nitrogen use efficiency, or calories produced per g of nitrogen input, and the environmental impacts of non-rice cereal crops. Regression lines are reciprocal fits between nitrogen use efficiency and a food's environmental impact. All relationships are significant at $p < .05$ except for acidification potential.

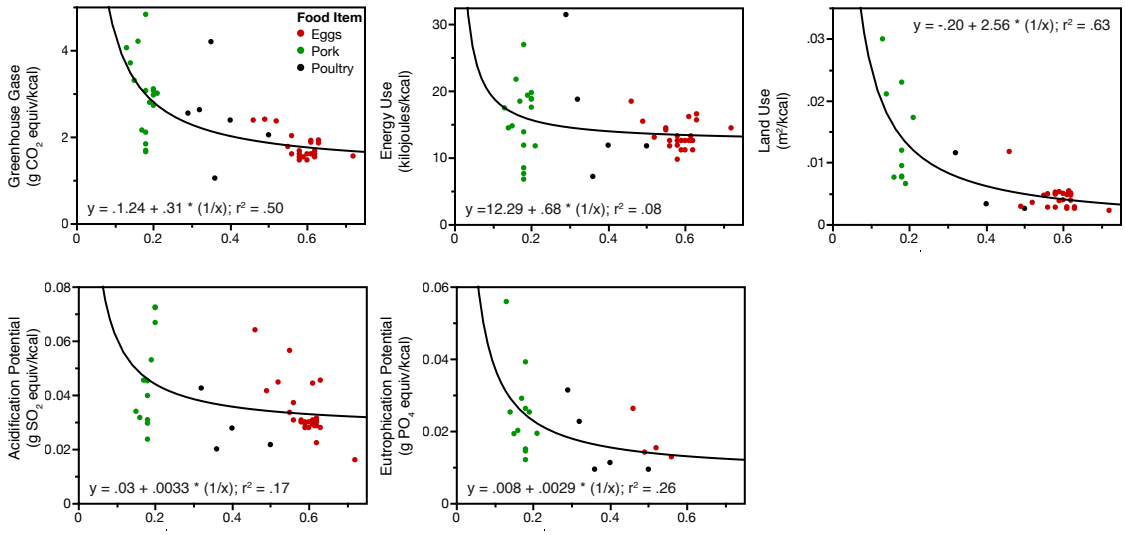

Figure 7. Correlations between feed use efficiency, or kcal of food produced per kcal of feed input, and environmental impacts in non-ruminant livestock systems. Regression lines are reciprocal fits between feed use efficiency and a food's environmental impacts. All relationships are significant at $p < .05$.

Several technologies and management techniques can increase agricultural input efficiency. Precision farming, where nutrient and pesticide inputs are temporally and spatially applied to match crop requirements, has increased fertilizer input efficiency and farmer profits without decreasing crop yields for a variety of crops in geographically diverse areas (Robertson & Vitousek, 2009). Conservation tillage and cover cropping, particularly with nitrogen fixing crops because they simultaneously reduce required nitrogen inputs, also increase fertilizer input efficiency by reducing nutrient loss from agricultural systems (Ponisio et al., 2014; Robertson & Vitousek, 2009). Feed input efficiency in livestock systems can also be increased. For example, pork from pigs fed diets supplemented with amino acids required less feed and emitted 5% fewer GHGs and had 28% lower eutrophication potential than pork from pigs fed unsupplemented diets (Ogino et al., 2013). Similar benefits have also been found in poultry, beef, and dairy systems (Robertson & Vitousek, 2009). In addition, using agricultural wastes and byproducts as animal feeds could reduce the environmental impacts of livestock production by 20% without reducing food quality or farmer profits (zu Ermgassen et al., 2016).

The location of food production can also influence its environmental impact because differences in climatic and soil conditions often affect agricultural input efficiency. Indeed, spatially locating food production in areas with the most suitable climatic and soil conditions for a crop can increase agricultural input efficiency and decrease environmental impacts (Chaplin-Kramer et al., 2015; Johnson et al., 2014; Polasky et al., 2008). For example, preferentially locating agricultural land to maximize single ecosystem services would increase carbon stores by ~6 billion metric tonnes (worth ~$1 trillion 2012 USD; Johnson et al., 2014) and substantially decrease projected rates of

agriculturally-driven biodiversity loss (Chaplin-Kramer et al., 2015). Globally leveraging environmental and soil conditions to increase agricultural input efficiency could thus provide substantial environmental benefits.

Environmental Impacts of different foods:

Many analyses have shown that dietary choice can greatly influence the environmental impacts of the agricultural food system (Clune et al., 2017; de Vries & de Boer, 2010; Nijdam et al., 2012; Tilman & Clark, 2014), although these analyses were limited to animal-based foods or a single environmental indicator. Our analyses expand on these earlier studies and show that foods with low impact for one environmental indicator tend to have low impacts for all environmental indicators examined (Figure 8). Indeed, for all indicators examined, ruminant meat (beef, goat and lamb/mutton) had impacts 20 – 100 times those of plants while milk, eggs, pork, poultry, and seafood had impacts 2 – 25 times higher than plants per kilocalorie of food produced. This clear trend of ruminant meat having high impacts and other animal-based foods having intermediate impacts also holds when foods are examined per gram protein, USDA serving, or unit mass (Supplemental Figure 1). Isocaloric shifts from high-impact to lower-impact but nutritionally similar foods, such as shifts from ruminant meats to fish, pork, poultry, or legumes, would have large diet-related environmental benefits while also improving human health outcomes (Tilman & Clark, 2014). These dietary shifts, however, would likely decrease the total cost of the diet; it is possible that increased consumption of other material goods could offset the environmental benefits of consuming lower-impact foods.

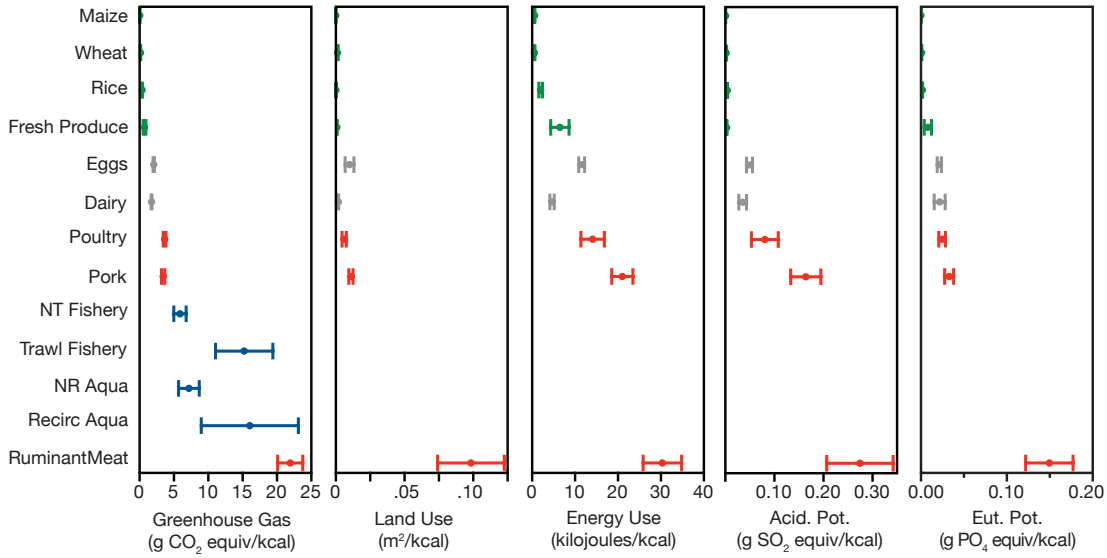

Figure 8. Environmental impacts of broad groups of foods per kilocalorie. The environmental indicators examined are greenhouse gas emissions, land use, energy use, acidification potential (Acid. Pot.) and eutrophication potential (Eut. Pot.). Bars show means and standard error. Plant-based foods are in green; dairy and eggs are in grey; meats are in red; and seafood is in blue. Data from foods grown in greenhouses are not included when plotting this figure. Trawl Fishery = bottom-trawling fisheries; NT Fishery = all other fisheries (e.g. line, purse net, seine net, etc); Recirc Aqua = recirculating aquaculture; NR Aqua = non-recirculating aquaculture (e.g. pond, net pen, flow-through, etc).

Most of the 742 LCA food analyses used were based on high-input systems in Europe and North America; the results presented here are thus indicative of the impacts of high-input systems in developed nations. In contrast, the impacts of low-input systems common in developing nations are not yet well studied, although a recent analysis indicates that GHGs may be higher in these systems because of lower agricultural input efficiency (Herrero et al., 2013). LCA analyses on less-studied but nutritionally and culturally important foods such as quinoa, cassava, and millet, as well as analyses from additional regions and management regimes would provide further insight and a clearer understanding of the environmental impacts of different foods and systems globally.

Conclusions:

Our analyses show that the comparative environmental impacts of agricultural production systems differ depending on the systems, food, and environmental indicator examined. Per unit of food produced, organic systems had higher land use and eutrophication potential, tended to have higher acidification potential, did not offer benefits in GHGs, but had lower energy use; trawling fisheries emitted almost 3 times more GHGs than non-trawling fisheries; grass-fed beef required more land and tended to emit more GHGs than grain-fed beef; and high agricultural efficiency was consistently correlated with lower environmental impacts. Combining the benefits of different production systems, for example organic's reduced reliance on chemical inputs with the high yields of conventional systems would result in a more sustainable agricultural system.

Agricultural input efficiency, or the amount of food produced per unit of input, is inversely correlated with a food's environmental impact in non-rice cereal systems and non-ruminant livestock systems. Increasing agricultural input use efficiency would have environmental benefits without necessitating dietary change. However, because the marginal environmental benefits of increasing agricultural input efficiency is larger in less efficient systems, special emphasis should be placed on improving efficiency in the least efficient agricultural systems.

The difference in environmental impacts between foods is large compared to the difference between production systems and systems with different agricultural input efficiencies producing the same food. Ruminant meats, for example, have impacts that are 3-10 times those of other animal-based foods and 20-100 times those of plant-based foods for all indicators examined. Because the majority of production systems included in these analyses are from Europe and North America, the results presented here are indicative of trends in highly industrialized and high-input agricultural systems. Analyses of the environmental impacts of low-input agricultural systems are necessary to elucidate

the extent to which the trends observed here also apply to lower-input agricultural systems.

The analyses presented here greatly expand current knowledge of the environmental impacts of food production. However, there are still large knowledge gaps which, if addressed, would further our understanding of food's environmental impacts. For example, analyses on the environmental impacts of agricultural systems in low-income countries, on staple crops not common in Westernized diets (quinoa, yams, sorghum, millet, etc), on fish produced via aquaculture, and on agricultural input efficiency in non-cereal crops and in ruminant systems are limited. In addition, agricultural production has a multitude of environmental impacts beyond the five environmental indicators analyzed here; few LCAs analyses have examined agriculture's other environmental impacts such as water use, pesticide use, or impact on biodiversity. Analyses into these, and other, under-studied aspects of agriculture's environmental impacts are needed to more fully elucidate agriculture's entire environmental impact.

Despite current knowledge gaps, it is clear that current agricultural trajectories would substantially increase agriculture's environmental impacts by midcentury (Bajzelj et al., 2014; Tilman et al., 2001; Tilman et al., 2011; Tilman & Clark, 2014). Many interventions would, however, greatly reduce agriculture's future environmental impacts. Adoption of low-meat and no-meat diets in nations with excess meat consumption (Springmann et al., 2016), sustainable increases in crop yields (Foley et al., 2011; Mueller et al., 2012), and adoption of low-impact and otherwise more efficient agricultural systems (Robertson & Vitousek, 2009), would offer large environmental benefits. In addition, over 30% of food production is wasted; reducing food waste would offer environmental benefits without requiring shifts in production practices or diets (Foley et al., 2011). Implementing policy and education initiatives designed to increase adoption of lower-impact foods, of lower-impact production systems, and of systems with high agricultural input efficiency is necessary before agriculture causes substantial, and potentially irreversible, environmental damage.

Chapter 3: The health and environmental impacts of major food groups

Abstract:

Diets are a leading source of poor human health and environmental harm, and without dedicated changes, will continue shifting to become less healthy and less environmentally sustainable. Information on the joint health and environmental impacts of various types of food is essential for informed consumer decisions and public policy. Using data on the health and environmental impacts of thirteen major food groups, we show that foods associated with improved health (minimally processed plant-based foods and fish) have lower environmental impacts than most other foods, whereas some foods associated with the greatest increases in disease risk have environmental impacts ~10-200x greater than those of healthier foods (red meats). Foods associated with no change in health (chicken, dairy, and eggs) have intermediate environmental impacts. The exceptions are added sugars and some other processed plant-based foods that are associated with increased disease risk but low environmental impacts. These trends are consistent across four health outcomes – total mortality and incidences of heart disease, diabetes, and stroke – and the four environmental indicators – greenhouse gas emissions, land use, irrigation water use, and eutrophication – examined here. Finding ways to increase consumption of healthier and more sustainable foods while decreasing consumption of less healthy or less sustainable foods could place humanity on a pathway towards a healthier and more sustainable future.

Introduction:

Dietary choices are the leading source of poor human health and environmental degradation globally. Nine of the top fifteen risk factors for morbidity are related to poor dietary quality and, in total, imbalanced diets have become the leading source of morbidity and mortality both globally and in most geographic regions of the world (Forouzanfar et al., 2015). At the same time, food production emits ~19-29% of global greenhouse gas emissions (GHGs; Vermeulen et al., 2012); occupies ~40% of Earth's land surface (FAO, 2017); causes nutrient pollution that has profoundly altered Earth's

ecosystems (Vitousek et al., 1997); and accounts for ~70% of Earth's freshwater withdrawals from rivers, reservoirs, and ground water (Molden, 2007). Further, diets globally are shifting in ways that, if not reversed, would rapidly decrease human and environmental health over the coming decades as populations become more affluent and urbanized and the global population increases (Springmann et al., 2016; Tilman & Clark, 2014).

Here we synthesize the health and environmental impacts of foods for four different health outcomes and four aspects of environmental degradation. Past analyses of links between diets, health, and the environment have focused on the impacts of alternative diets, such as a Mediterranean or vegetarian diets, relative to the usual Western diet (e.g. Tilman and Clark 2014; Springmann et al 2016). However, determining the health and environmental impacts of individual food types would provide policy makers, food industries, and consumers with detailed information to guide decision making.

We first examine how consumption of each of 13 food groups is associated with four different health outcomes – the risk of total mortality and the incidences of coronary heart disease (CHD), diabetes, and stroke – by using results from 23 recent diet and health meta-analyses (Abete et al., 2014; Afshin et al., 2014; Aune et al., 2016a, 2016b, 2017, 2013a, 2013b; Chen et al., 2013; Feskens et al., 2013; Huang et al., 2014; Imamura et al., 2015; Larsson & Orsini, 2011; Mullie et al., 2016; Rong et al., 2013; Tasevska et al., 2014; Wallin et al., 2012, 2016; Wang et al., 2015; Wu et al., 2015; Xi et al., 2015; Yang et al., 2014; Zhao et al., 2015; Zheng et al., 2012). By controlling for potentially confounding factors of disease risk such as socioeconomic and demographic variables, these analyses examine how daily consumption of an additional serving of a given food is associated with each health outcome (Supporting Information; **Supplemental Table 2; Figure S1**). Using data from recent environmental analyses (Clark & Tilman, 2017; FAO, 2017; Mekonnen & Hoekstra, 2010), we then summarize and synthesize the environmental impacts of producing a serving of a given food for four different environmental indicators – greenhouse gas emissions (GHGs), land use, irrigation water

use, and eutrophication (nutrient pollution associated with application of fertilizers) (**Figure S2**). We then use the relationships between the health and the environmental impacts of these 13 food types to classify foods that are healthy and more sustainable as well as those that are less healthy or less sustainable

Associations between health and environmental impacts

When examining the average health and environmental impact across four health impacts and disease outcomes, there is, with the exception of added sugars and sugar-sweetened beverages (SSBs), a significant tendency for foods that have a lower environmental impact to also be healthier, and vice versa (Figure 1). Added sugars and SSBs have low environmental impacts, but are also associated with increased disease risk. Daily consumption of minimally processed plant-based foods such as whole grain cereals, fruits, vegetables, legumes, and nuts are associated with improved health and have low environmental impacts; fish consumption is also associated with improved health and has low to intermediate environmental impacts; dairy, eggs, and chicken are associated with no significant change in health and have intermediate environmental impacts; and consumption of unprocessed and processed red meats (pork, beef, mutton, and goat meet) is associated with increased disease risk and has environmental impacts 20-200x those of minimally processed plant-based foods (**Figure 1**).

We also examined the associations between each health and all environmental outcomes (**Figure 2**), all health and each environmental outcome (**Figure 3**), and each health and each environmental outcome (**Figure S3**) because foods may differ in their health outcome between disease endpoints and in their environmental impact across environmental indicators. Doing this shows that there are five major food types that often differ from each other in their impact on human health and the environment. The health and environmental impact of these five food types – minimally processed plant-based foods; fish; chicken, dairy, and eggs; red meat; and sugars – are discussed in more depth below.

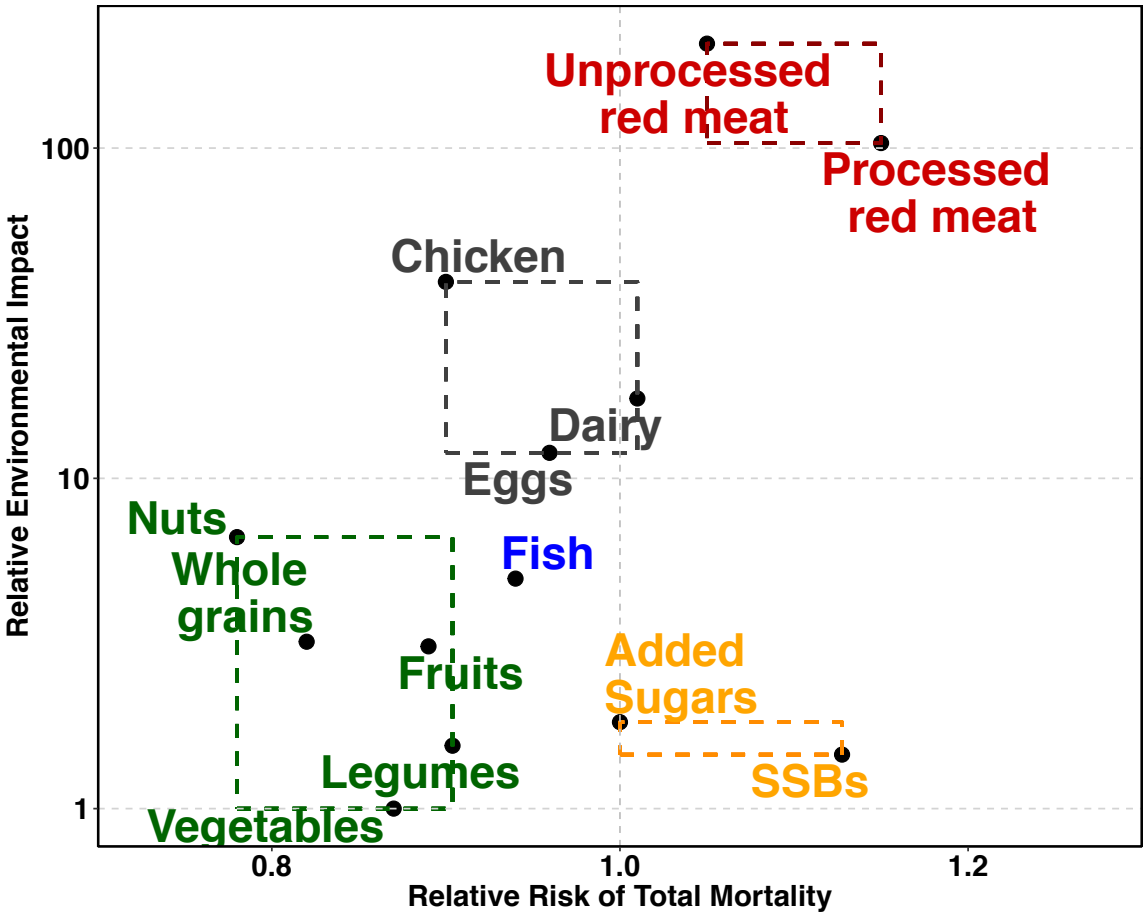

Figure 1. Association between risk of mortality and the averaged environmental impact of different foods across four environmental indicators. Bounding boxes indicate the range of mortality risk and environmental impact of different food groups. Text and bounding boxes are colored where green = minimally processed plant-based foods; blue = fish; grey = chicken, dairy, and eggs; red = red meats; and orange = sugars. Relative risk of mortality is reported as the relative risk of disease per serving of food consumed per day, where a relative risk > 1 indicates that a food is associated with increased disease risk and a relative risk < 1 indicates that a food is associated with decreased disease risk. The average environmental impact is reported as the environmental impact relative to a serving of vegetables.

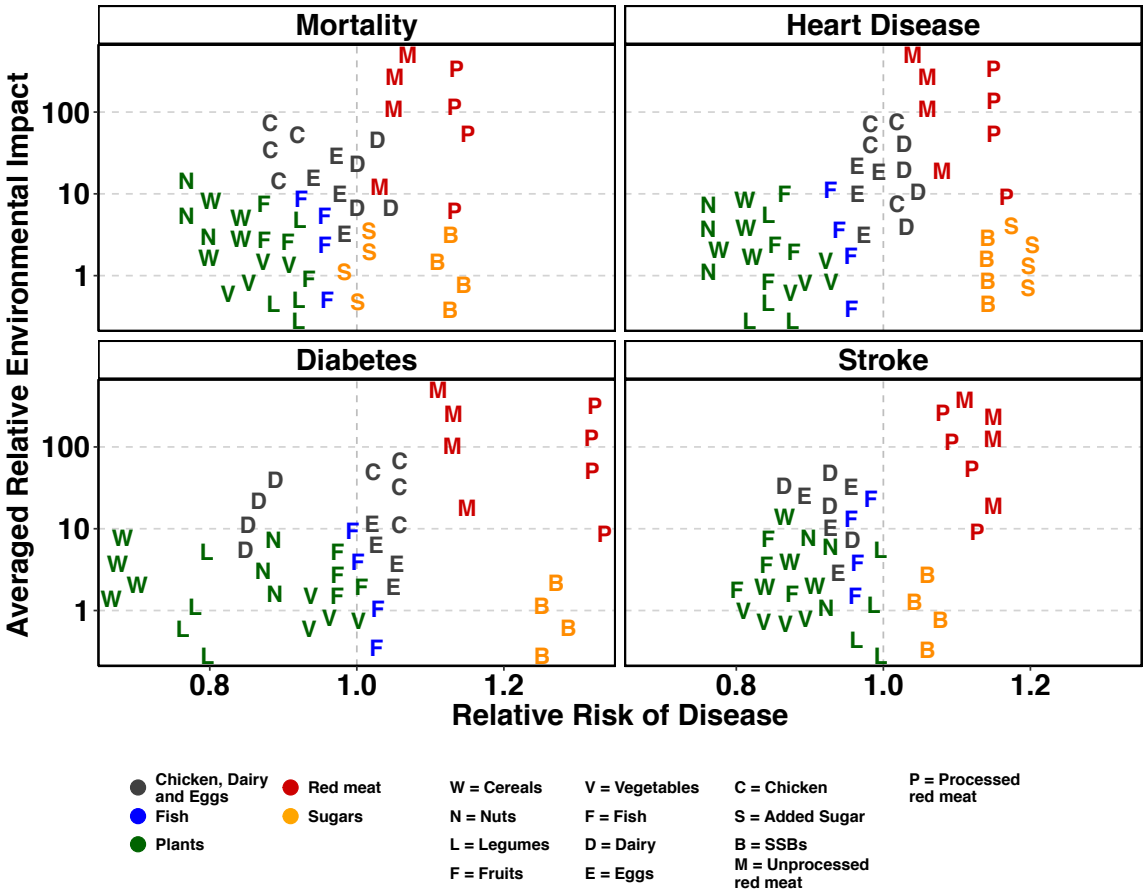

Figure 2. Association between four health endpoints and the averaged environmental impact across four environmental indicators for 13 food groups. Letters denote food type, are jittered to avoid overlap, and are colored where green = minimally processed plant-based foods; blue = fish; grey = chicken, dairy, and eggs; red = red meats; and orange = sugars. The health impact is reported as the relative risk of disease per serving of food consumed per day, where a relative risk > 1 indicates that a food is associated with increased disease risk and a relative risk < 1 indicates that a food is associated with decreased disease risk. The average environmental impact is reported as the environmental impact relative to a serving of vegetables.

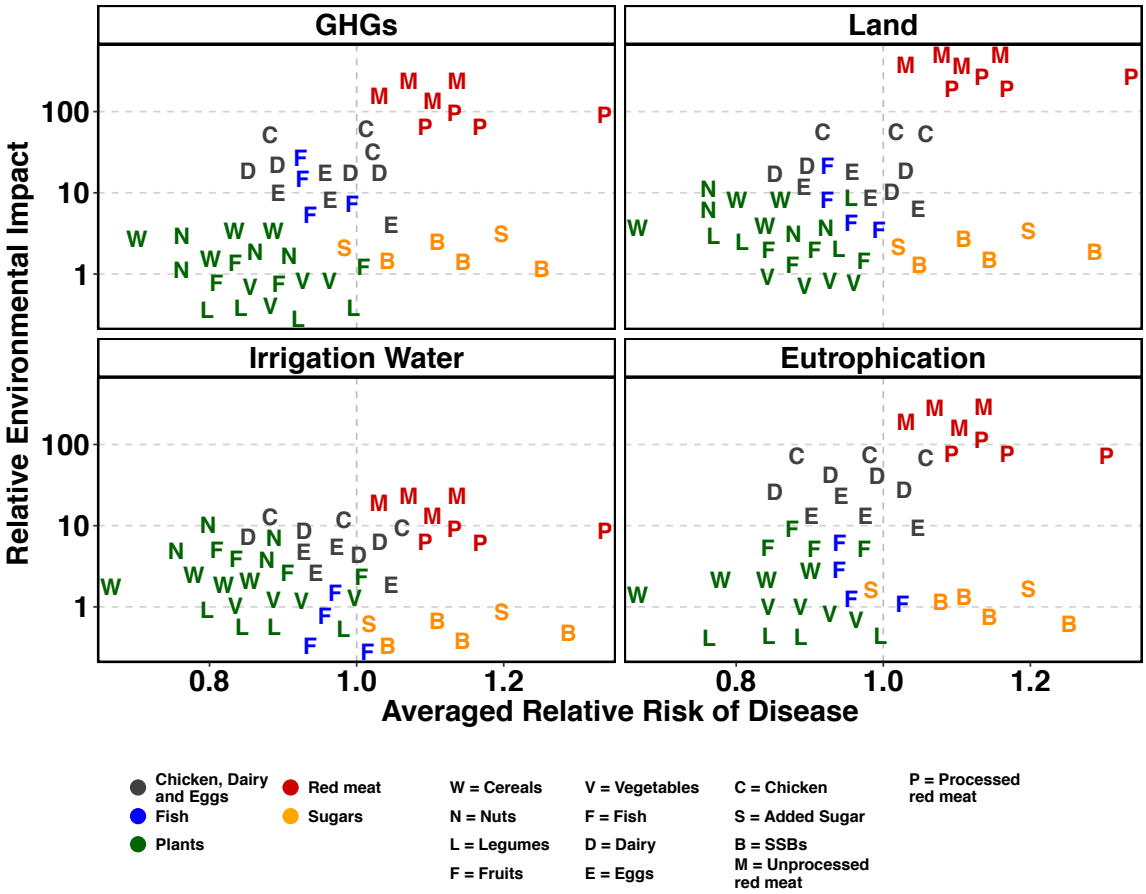

Figure 3. Association between four environmental indicators and the average health impact across four health endpoints for 13 food groups. Letters denote food type, are jittered to avoid overlap, and are colored where green = minimally processed plant-based foods; blue = fish; grey = chicken, dairy, and eggs; red = red meats; and orange = sugars. The health impact is reported as the relative risk of disease per serving of food consumed per day, where a relative risk > 1 indicates that a food is associated with increased disease risk and a relative risk < 1 indicates that a food is associated with decreased disease risk. The average environmental impact is reported as the environmental impact relative to a serving of vegetables.

Plants

Consumption of a daily serving of whole grain cereals, nuts, legumes, fruits, and vegetables is often associated with a significant reduction in disease risk, and in no case

is associated with increased disease risk (Figures 1, 3). Whole grain cereals, nuts, fruits, and vegetables are associated with significant reductions in total mortality. Whole grains and nuts have large effects for modest amounts of daily consumption (~17% risk reduction per 90g of whole grains (Aune et al., 2016b); ~22% reduction per 28g of nuts (Aune et al., 2016a). Whole grains and nuts are associated with large and significant decreases in diabetes incidence; whole grains, nuts, legumes, fruits, and vegetables are associated with significant decreases in CHD risk; and fruits and vegetables are associated with a significant decrease in stroke risk (whole grains, nuts, and legumes are also associated with mean reductions in stroke risk, although this relationship is not significant). The health benefit of consuming minimally processed plant-based foods is often non-linear: increasing consumption of whole grain cereals when >100g/day are already consumed is associated with smaller additional health benefits (Aune et al., 2016b) than increasing whole grain consumption when <100g/day are consumed, while increasing consumption of fruits or vegetables is associated with smaller additional smaller health benefits when >300g/day are already consumed (compared to <300g/day), although health benefits are observed up to ~800g/day (Aune et al., 2017).

Minimally processed plant-based foods often have among the lowest environmental impacts of all foods examined here. For instance, legume production has particularly low GHG emissions and nutrient runoff, largely because of their ability to fix nitrogen and resultant low fertilizer inputs while producing a serving of fruits or vegetables requires the least amount of land of all foods examined here. Nuts have lower water use per serving than beef, lamb, pork and chicken (Fig. 5), but higher other foods, and some irrigated tree nuts produced in arid regions may place stresses on water resources similar to those of livestock.

Fish

Fish consumption is associated with reduced risk of total mortality and incidences of heart disease and stroke (Larsson & Orsini, 2011; Zhao et al., 2015; Zheng et al., 2012). Fish type and preparation method are likely mediators of the health benefit of consuming

fish: oily fish (e.g. salmon, mackerel, tuna, etc) are associated with more beneficial health outcomes than white fish (e.g. cod, hake, pollock, etc), while consuming fish after it has been fried may negate the potential health benefits of fish consumption (Wallin et al., 2012). Fish-derived fatty acids, a potential moderator of their health benefits, can also be found in plant-based foods such as nuts and seeds (Del Gobbo et al., 2016).

The environmental impact of fish production is highly dependent on production methodology. Wild-caught fish occupy no land and use no irrigation water, but poor management of wild-caught fisheries may lead to over-fishing and fishery collapse (FAO, 2016) Some aquaculture systems also use no land or irrigation water (e.g. mussel production), although aquaculture production, on average, occupies ~10-15x more land and requires ~1.5x more irrigation water than vegetables primarily because of the plant-based feed used when raising fish in aquaculture. Aquaculture feeds that include a larger portion of fish feed would use less land and require less water, but could possibly increase pressure on wild fisheries. Both wild-caught and aquaculture-grown fish vary in their GHG emissions; trawling fisheries (where nets are dragged across the seabed) and recirculating aquaculture (where water is consistently filtered and circulated between tanks) emit ~3x more GHGs than other fishery and aquaculture production methods because of their higher energy requirements.

Chicken, Dairy, and Eggs

Chicken, dairy, and eggs are not associated with a significant change in health for any disease endpoint examined here. Although dairy intake has also been promoted for bone health because of its calcium content, increased dairy consumption is correlated with either no change (Feskanich et al., 2003) or an increased risk (Michaelsson et al., 2014) of bone fracture, while regions with the highest levels of dairy consumption often have the highest rates of hip fracture (Abelow et al., 1992; Hegsted, 2001). Skim and whole-fat dairy products may differ in their health outcomes (Aune et al., 2013a), although evidence is limited and often contradictory (see Mullie et al (2016) for a more in-depth discussion). While egg consumption is not associated with health outcomes for average

individuals, egg consumption is associated with increased risk of CHD for individuals with pre-existing diabetes (Rong et al., 2013). Substituting chicken or low-fat dairy for unprocessed or processed red meat is associated with decreased risk of mortality (Pan et al., 2012b), but disease risk can be further reduced by substitution with plant-based foods (Bernstein et al., 2010; Bernstein et al., 2011, Pan et al., 2011; Pan et al., 2012).

Producing a serving of chicken, dairy, or eggs also has intermediate environmental impacts: dairy and egg production both have environmental impacts ~10x higher than a serving of vegetables; chicken production has higher impacts than dairy and eggs, resulting in ~50x more GHG emissions, land use, and nutrient runoff, and ~10x more irrigation water use than a serving of vegetables.

Added Sugars

Consumption of added sugar is often associated with increased disease risk. Added sugar consumption is associated with a significant increase in risk of diabetes of diabetes (Imamura et al., 2015), CHD (Huang et al., 2014; Yang et al., 2014), and stroke (Xi et al., 2015). Added sugar consumption has not been associated with risk of total mortality in meta-analyses (Tasevska et al., 2014), but has been associated with increased risk of total mortality from cardiovascular disease in individual cohorts (Yang et al., 2014). Sugar-sweetened beverages are associated with a significant increase in risk of diabetes (Imamura et al., 2015) and CHD (Huang et al., 2014), and SSB consumption is also associated with elevated stroke risk (Xi et al., 2015) although this association is not significant.

Producing added sugars and SSBs has low environmental impacts. They use similar amounts of water and cause a similar amount of eutrophication as a serving of vegetables, but emit ~2-5x more GHGs and require ~2-5x more land. However, sugar production, which often occurs in tropical region, can result in deforestation and emit large amounts of GHGs (Tilman & Clark, 2014) and might lead to biodiversity loss (Tilman et al., 2017).

Red Meat

Unprocessed and processed red meat are associated with increased disease risk and large environmental impacts for all health endpoints and environmental indicators examined here (Chen et al., 2013; Feskens et al., 2013; Wang et al., 2015). Consuming a serving of processed red meat per day is associated with significant increases in all four disease endpoints examined here, and has a particularly large impact on risk of total mortality (~15% increase per 50g per day) and diabetes (~32% increase per 50g per day). Unprocessed red meat is also associated with increased mean risk of disease for all health endpoints included here, although this association is not significant for risk of total mortality and incidence of CHD. Consumption of processed red meat is associated with more negative health outcomes than unprocessed red meat, perhaps because it often has higher concentrations of nitrite, nitrate, and sodium than unprocessed red meat (Etemadi et al., 2017), although it is possible to process meat without using nitrite, nitrate, or sodium by e.g. fermenting or smoking meat. Although we did not systematically assess the associations of foods and cancer risk, consumption of unprocessed and processed meat are associated with increased cancer incidence (Bouvard et al., 2015; Chan et al., 2011).

Producing a serving of unprocessed or processed red meat has the largest environmental impact of every indicator examined here: they emit ~100x more GHGs, require >100x more land, result in ~100x more eutrophication, and use ~10x more irrigation water than a serving of vegetables. The environmental impact of different red meats varies; ruminant meat (beef, sheep, and goat) production emits ~5.5x more GHGs, requires 6.5x more land, results in ~3x more eutrophication, and uses ~1.5x more irrigation water than pork. Grass-fed and grain-fed beef differ in their environmental impacts; per unit of food produced, grass-fed beef production requires more land, results in larger amounts of nutrient pollution, and emits more GHGs, although carbon sequestration may offset the GHG emissions from grass-fed beef production, although uncertainties around the amount of potential carbon sequestration remain large (Garnett et al., 2017). Clearing

land for pastures has detrimental impacts for biodiversity and ecosystem functioning, although properly managed grass-fed systems on existing grasslands and pasturelands can improve nutrient cycling and increase food security in areas with limited amounts of cropland (Smith et al., 2013).

Pathways to a healthier and more sustainable future

These analyses show that minimally processed plant-based foods are associated with improved health and have low environmental impacts; that fish is associated with improved health and has low to intermediate environmental impacts; that chicken, dairy, and eggs are not associated with health endpoints and have intermediate environmental impacts; that added sugars are associated with increased disease risk but have low environmental impacts; and that red meat is associated with increased disease risk and has the highest environmental impact of any food examined.

Furthermore, these analyses show that, with the exception of added sugars and SSBs, foods associated with increased risk of disease often also have environmental impacts an order of magnitude or more larger than foods associated with reduced disease risk. However, simply consuming larger quantities of healthier and lower-impact foods is neither healthy nor sustainable; excess caloric consumption and resultant weight gain leads to negative health outcomes (Whitlock et al., 2009) while excess caloric consumption increases diet-related environmental impacts. Instead, foods that are healthy or lower-impact should be substituted for less-healthy or higher-impact foods.

Diets globally are shifting to include more sugar, chicken, dairy, eggs, red meat, and calories in general – which are often associated increased disease risk and/or higher environmental impacts than minimally processed plant-based foods. Policy initiatives designed to slow current dietary shifts and instead increase consumption of healthier and more sustainable foods would likely improve diet-related health and environmental outcomes. Taxation (Cochero et al., 2017), food labeling (Vanclay et al., 2011), education initiatives (Hawkes et al., 2015), and changes in the food environment

(Hawkes et al., 2015) have already been effective at shifting diets towards healthier and more sustainable outcomes and would likely offer further benefits if more widely adopted (Springmann et al., 2016). Finding a suite of policy initiatives that are culturally, socially, politically, and economically appropriate that shift diets towards healthier and more sustainable foods could place humanity on a pathway towards a healthier and more sustainable future.

Methods:

Health Impacts

The health impact of food consumption for total mortality and incidences of CHD, stroke, and diabetes were obtained from recent meta-analyses that examined the marginal health impact of consuming an additional serving of food per day (**Supplemental Table 1; Figure S1a**). The health analyses controlled for potential confounding factors that may also be associated with health outcomes such as lifestyle factors (e.g. history of smoking, physical activity), dietary patterns (e.g. consumption of processed meat, multi-vitamin use), socioeconomic variables (e.g. education, annual income), history of disease (e.g. diabetic), sex, ethnicity, age, height, and weight. Publications with authors funded by industry groups were not included in this analysis because of potential biases. See **Supplemental Table 1** for a list of publications included in this analysis.

Data on risk of total mortality was missing for legumes, eggs, and SSBs. To estimate the RR of total mortality, we weighted the RR for disease-specific endpoints based on their individual relative contributions to global mortality.

Environmental Impacts

Greenhouse gas emissions, land use, and eutrophication potential per gram of food produced were obtained from a recent meta-analysis of life cycle analyses (Clark & Tilman, 2017) and supplemented with land use data from the FAO (FAO, 2017) while irrigation water use was obtained from a global analysis using life cycle analysis methodology (Mekonnen & Hoekstra, 2010). Because food groups (e.g. cereals, red

meat) often include multiple types of food, the average environmental impact per gram of each food group was weighted based on current global consumption patterns of the foods within the food group. To estimate the environmental impacts per serving of food produced, the environmental impact per gram of food produced was then paired with the serving size reported in the health meta-analyses (**Figure S2; Supplemental Data**).

To better compare the relative magnitude of environmental impact of different foods, and because the magnitude of a food's environmental impact varies across environmental indicators, we then calculated the environmental impact for each food and indicator relative to the environmental impact of vegetables per serving of food produced. As such, a food with a relative environmental impact of 0.5 has an environmental impact ½ that of a serving of vegetables, whereas a food with a relative environmental impact of 25 has an environmental impact 25x larger than a serving of vegetables.

Associations between health and environmental impacts

To examine the association between the health and environmental impact of food, we first plotted the relative risk of disease (RR) against the relative environmental impact of each food for each health endpoint and each environmental indicator (**Figure S3**).

To calculate the average health or environmental impact of a food, we averaged the reported RR across all health endpoints examined here or the relative environmental impact across all environmental indicators examined here, respectively.

To compare the health and environmental impact of each food, we then compared RR of total mortality risk against the averaged relative environmental impact (**Figure 1**), the averaged relative environmental impact against the RR for each health endpoint (**Figure 2**), and the averaged RR against each environmental indicator (**Figure 3**).

Chapter 4: Agricultural expansion and its projected impact on bird diversity in Sub-Saharan Africa

Abstract:

The rate of biodiversity decline across the world is accelerating, largely because agricultural expansion – the world's leading threat to biodiversity – is occurring in highly diverse regions. Although much of the biodiversity in Sub-Saharan Africa is not yet greatly threatened, Sub-Saharan Africa is a region of particular concern because of large projected increases in agricultural land demand. To forecast how agricultural expansion might affect the future of biodiversity in Sub-Saharan Africa, we link forecasts of agricultural expansion to biodiversity outcomes for 2,072 bird species in Sub-Saharan Africa at spatial scales relevant to ecological function, agricultural production, and conservation actions. We project that agricultural expansion by 2060 will drive a net decline of ~30% of the currently remaining area of habitat across all species, with larger declines projected across the equatorial forest, the eastern coast, and in Madagascar; for species with a current Red List classification of "Critically Endangered" or "Endangered"; for habitat specialists; for species found predominantly in forests; and for species that are intolerant of agricultural activities. Scenarios that reduce agricultural expansion by closing yield gaps, reducing meat consumption, or shifting agricultural production to higher-yielding regions could prevent ~15-48% of expected declines in area of remaining habitat, while simultaneous implementation of these scenarios would avoid >80% of projected declines in remaining area of habitat. These results show that while agricultural expansion will likely drive large decreases in area of habitat for bird species across Sub-Saharan Africa, swift implementation of proactive policies to reduce agricultural expansion could avoid much of the projected declines in remaining area of habitat.

Introduction:

The rate of biodiversity decline across the world is accelerating (Ceballos et al., 2015; Pimm et al., 2014; WWF, 2016). Conventional conservation approaches have had many successes (Hoffmann et al., 2010; Rodrigues, 2006), but adequately protecting all species

and sites would require funding to be increased by an order of magnitude (McCarthy et al., 2012) and the extent of land safeguarded for nature to be more than doubled (Butchart et al., 2015). The future of biodiversity is therefore likely to depend on coupling increased conventional conservation efforts with concerted efforts to reduce the drivers of biodiversity declines (Tilman et al., 2017).

Sub-Saharan Africa is a region of particular conservation concern. While biodiversity is not yet greatly threatened in Sub-Saharan Africa, previous analyses have projected that agricultural expansion – the world's leading threat to biodiversity – will likely have a large and negative impact on biodiversity in Sub-Saharan Africa (IUCN, 2017; Newbold et al., 2015; Tilman et al., 2017; Visconti et al., 2011; Visconti et al., 2016). Although these analyses have made important contributions to our understanding of how agricultural expansion will likely threaten biodiversity in the future, their utility for conservation planning and action has been limited by coarse spatial scales; by often focusing only on mammals; or by investigating broad development pathways rather than changes to specific aspects of the food system (Newbold et al., 2015; Tilman et al., 2017; Visconti et al., 2011; Visconti et al., 2016).

We expand on these previous analyses by forecasting how agricultural expansion in Sub-Saharan Africa will affect the remaining area of habitat (AOH, formerly ESH; Beresford et al 2011; Rondinini et al 2011) for 2,072 bird species and subspecies (1,827 species) at ecologically, economically, and conservation-relevant scales (1.5km by 1.5km cells). To do this, we first used a two-stage modelling process to model a 5-year interval of historic spatial patterns of agricultural expansion. We then linked this modelling process to forecasts of future agricultural land demand to project spatial patterns of agricultural expansion at 5-year time intervals through 2060. The spatial forecasts of agricultural expansion were then linked to habitat suitability models (e.g. Rondinini et al. 2011) to forecast species-level changes in remaining AOH. Finally, we repeated this process for four alternative scenarios where policy outcomes have reduced agricultural land expansion. This framework enables us to not only highlight the regions and species most

at risk from agricultural expansion, but also the extent to which policy outcomes that reduce agricultural expansion might reduce future declines in remaining AOH.

Forecasting Spatial Patterns of Land Expansion

We modeled historical patterns of agricultural expansion at 2.25km^2 resolution using a two-stage modeling process based using historic MODIS satellite land cover data (DAAC, 2017). In the first stage, we used a multinomial model to quantify how the amount of cropland or pastureland had changed in a cell based on its proximity to other agricultural land (DAAC, 2017), travel time to cities (Weiss et al., 2018), its suitability for crop production (FAO & IIASA, 2017), whether it contains any amount of a protected area (UNEP & IUCN, 2017), and previous changes in the amount of agricultural land in the cell (DAAC, 2017). In the second stage, we then used these estimated parameters to forecast the amount of change in agricultural land in a cell using the same predictor variables in a generalized linear model. We combined this two-stage modeling process with country-specific estimates of agricultural land demand at five year intervals from 2010 to 2060 (Tilman et al., 2017), and then probabilistically selected cells to experience a change in agricultural land until a country's forecasted five year target of agricultural land demand has been met. We used this two-stage process to forecast the location of cropland and pastureland, and repeated the forecasts 10 times because the land expansion model is probabilistic. See supplemental methods for more detail.

In the Business-As-Usual (BAU) scenario, we project large increases in cropland throughout Sub-Saharan Africa, particularly across the equatorial forest, along the southern border of the Democratic Republic of the Congo, and along the eastern coast (e.g. Zimbabwe, Malawi, and Tanzania). We also project large changes in the location of pastureland, with decreases along the southern edge of the Saharan Desert, throughout the equatorial forest, and along the eastern coast, and small increases along the borders of the Democratic Republic of the Congo (Figure 1). Despite differences in methodologies, our forecasts of the spatial location of future agricultural land are similar to existing forecasts (e.g. (Van Asselen & Verburg, 2013).

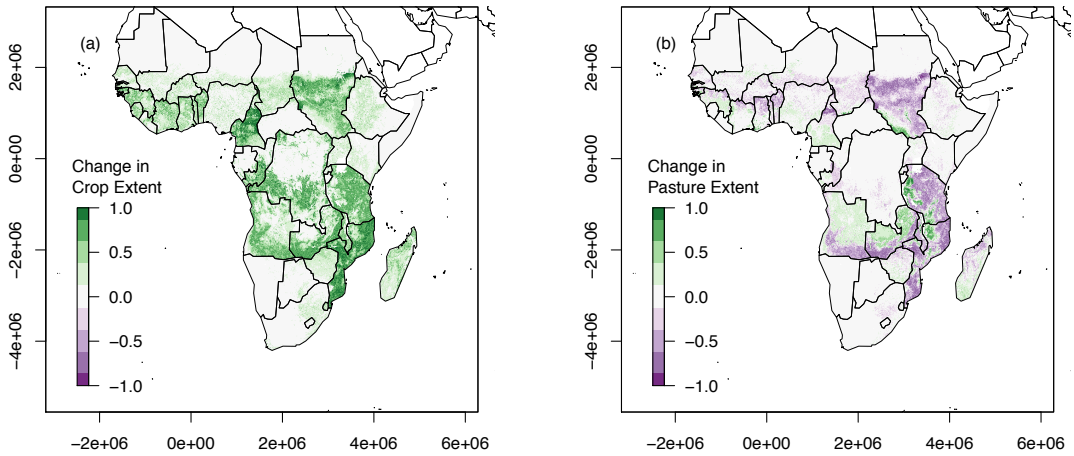

Figure 1. Business-As-Usual projections of changes in (a) cropland and (b) pastureland extent from 2010 to 2060 at 1.5 x 1.5km resolution. Change in agricultural extent is measured in proportion of a cell (e.g. 0.1 = 10% increase in agricultural extent in that cell), where green denotes a projected increase in agricultural extent and purple denotes a projected decrease in agricultural extent. A value of 1 indicates that cropland or pastureland extent in that cell is projected to increase from 0 (e.g. cell does not currently contain cropland or pastureland) to 1 (the cell is entirely occupied by cropland or pastureland) whereas a value of -1 indicates that cropland or pastureland extent in that cell is projected to decrease from 1 (the cell is entirely occupied by cropland or pastureland) to 0 (e.g. cell does not currently contain cropland or pastureland). Countries in white were not included in the analysis.

Forecasting Future Threats to Biodiversity

We linked our model of agricultural expansion to existing habitat suitability models (e.g. (Ficetola et al., 2015; Rondinini et al., 2011), which estimate the remaining area of

habitat (AOH) for each species based on its original habitat range, habitat preferences, and tolerance of human activity (e.g. agricultural expansion). In doing so, we projected an average decline in remaining AOH of 28.9% (median = 28.2%) for bird species in Sub-Saharan Africa by 2060 in the Business-As-Usual scenario. In addition, we projected that 1374 species and subspecies (~66.3% of species examined) are likely to lose >= 10% of their remaining AOH; that 1117 species and subspecies (~53.9%) are likely to lose >25% of their remaining AOH; that 440 species and subspecies (~21.2%) are likely to lose >50% of their remaining AOH; that 141 species and subspecies (~6.8%) are likely to lose >75% of their remaining AOH; that 78 species and subspecies (~3.8%) are likely to lose >90% of their remaining AOH; and that 35 species and subspecies (~1.7%) are projected to lose >99% of their remaining AOH.

Declines in remaining AOH are projected to be highly spatial (Figure 2a); declines of >25% in remaining AOH are projected across much of Western, South Central, and Southeastern Sub-Saharan Africa, with declines > 30% found primarily across South Central Sub-Saharan Africa and in Madagascar, and declines > 35% primarily found along the eastern coasts of Mozambique and Tanzania, as well as throughout Madagascar (Figure 2a). Declines are projected to be largest in these regions, possibly because they are projected to experience the largest amount of cropland expansion (Figure 1a), but perhaps also because of the high rate of endemic species in Madagascar. Smaller declines in remaining AOH are projected across the far Northern and Southern parts of Sub-Saharan Africa, likely because expansion of agricultural land is projected to be smaller in these regions.

Declines in remaining AOH are projected to be much greater amongst certain groups of species (Figure 3). Perhaps most alarming is that agricultural expansion is projected to disproportionately impact species that are currently most at risk of extinction(Figure 3a): species currently classified as “Critically Endangered” (projected mean decline of ~35.4% in AOH), “Endangered” (~35.5% decline), “Vulnerable” (~31.4% decline), or “Near Threatened” (~34.2% decline) by the IUCN Red List are projected to experience

larger declines in AOH compared to species currently classified as being of "Least Concern" (~28.0% decline). Furthermore, these declines are projected to be particularly rapid in the next two decades for species that are currently most at risk of. For example, ~69.6% of total declines in remaining AOH are projected to occur by 2030 for species classified as "Critically Endangered", compared to ~48.4% for species of "Least Concern".

Habitat specialists (~44.3% decline in remaining AOH; defined as species where only a single habitat is "suitable" as per IUCN Habitat Classification Scheme Level 2) are projected to experience larger declines in remaining AOH than are habitat generalists (~27.4% decline in AOH) (Figure 3b), while species not tolerant of agriculture (~44.0% decline in AOH; defined as species that cannot survive in either cropland or pastureland) are projected to experience larger declines in remaining AOH than are species that are either semi-tolerant (~19.7% decline in AOH) or tolerant of agriculture (0% decline in AOH), respectively (Figure 3c).

We projected smaller declines in remaining AOH for "large" (body mass >2kg) than for either "small" (body mass <= 0.5kg) or "medium" (body mass <=2kg and >0.5kg) bird species (Figure 3d). This differs from ecological theory (Cardillo et al., 2005) and previous analyses (e.g. (Tilman et al., 2017), where large species have been projected to experience larger increases in extinction risk than smaller-bodied species, because of their larger range sizes, because they are less tolerant to the interaction between different stresses to biodiversity (e.g. habitat fragmentation, habitat loss, and hunting), and because population-level responses to environmental changes are often slower than those of smaller species. Our results likely differ because we focused on the impact that agricultural expansion was projected to have on remaining AOH, and did not translate losses in AOH to changes in expected extinction risk; translating changes in remaining AOH to IUCN classification status might lead to more similar results to those of past analyses.

Projected declines in remaining AOH also differ across species with different habitat preferences: forest-dependent species are projected to experience the largest declines in remaining AOH (projected ~33.7% decline in AOH), whereas species found in deserts (~15.0% decline), subterranean (includes birds that nest in burrows; ~10.4% decline) and "other" habitats (~5.9% decline) are projected to experience the smallest reductions in remaining AOH (Figure 3e).

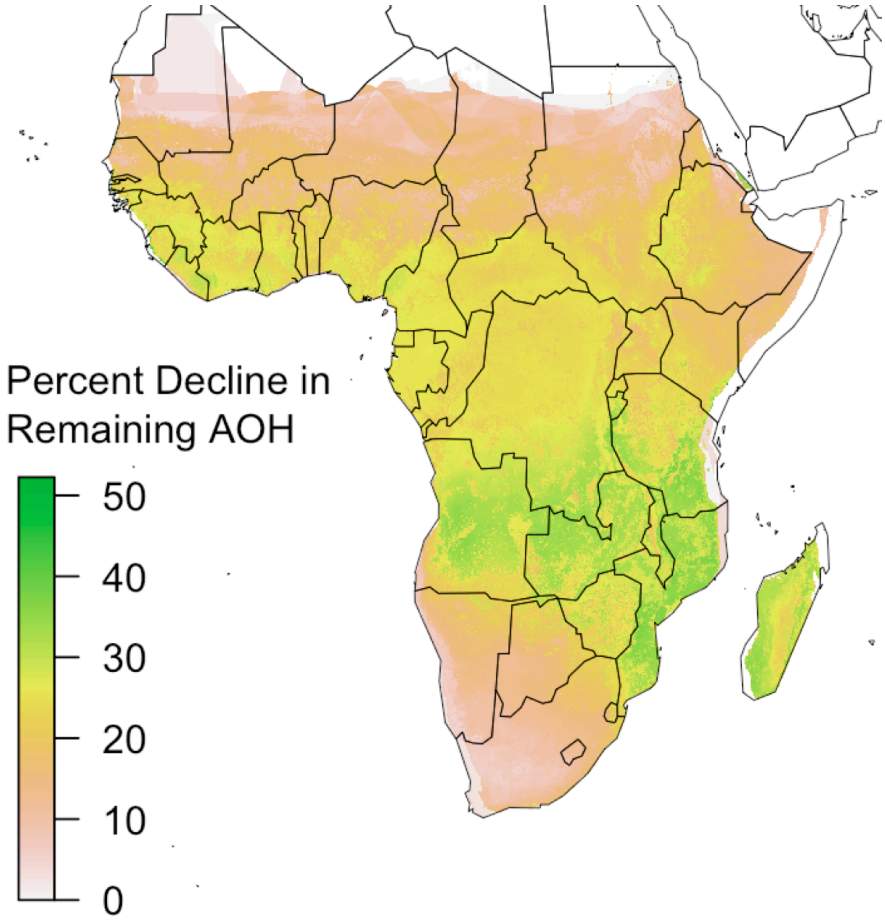

Figure 2. Projected percent decline in remaining area of habitat (AOH) from agricultural expansion by 2060. Decline in each 1.5x1.5 km^2 grid cell was calculated as the average decline in remaining area of habitat for all species that historically existed in a cell based on their tolerance to agricultural areas. See supplemental methods for more detail.

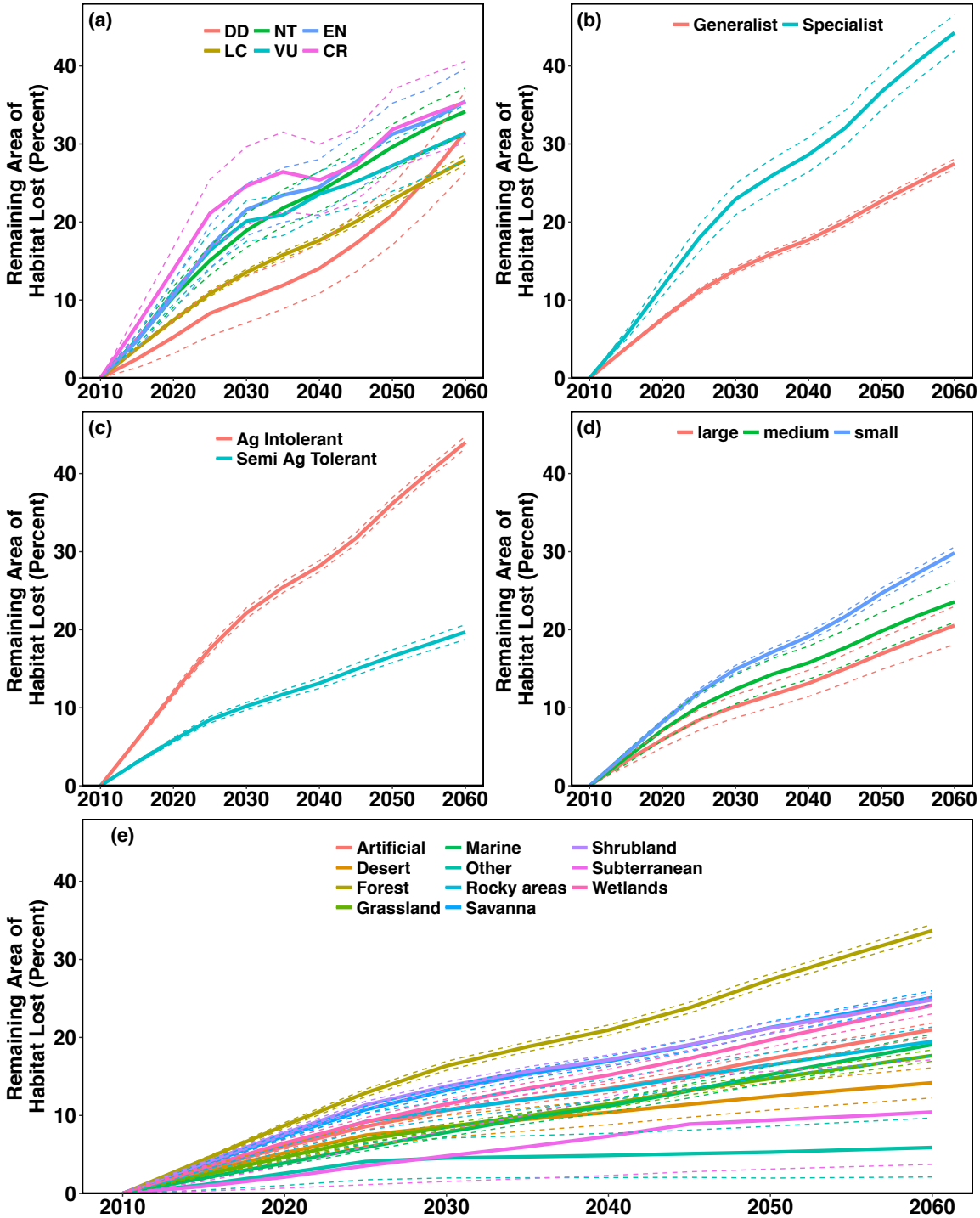

Figure 3. Projected declines in remaining area of habitat by (a) current IUCN classification, (b) habitat breadth, (c) tolerance to agriculture, (d) body mass, and (e) habitat preference. (a) IUCN classification is LC = least concerned, NT = near

threatened, VU = vulnerable, EN = endangered, and R = critically endangered. **(b)** Specialist species are defined as species with a single "suitable" habitat as per IUCN estimates of habitat suitability, generalist species have more than one "suitable" habitat. **(c)** Species intolerant of agriculture ("ag intolerant") are those that cannot exist in either cropland or pastureland whereas species moderately tolerant to agriculture ("semi ag tolerant") can exist in either cropland or pastureland. **(d)** body mass is defined where "large" is a body mass > 2kg, "medium" is a body mass <= 2kg and > 0.5kg, and "small" is a body mass <= 0.5kg. **(e)** Habitat preferences defined as per IUCN habitat classification scheme level 1 (IUCN 2017); species are considered to exist in a habitat if that habitat is classified as being "suitable" for that species. Percent of remaining area of habitat lost is calculated by the extent of cropland expansion within each species' original habitat range and that species' tolerance to agricultural areas. See supplemental methods for more detail. Dashed lines represent +- 1 standard error.

Approaches to Reduce Biodiversity Threats

We also examined how reducing agricultural land demand might affect future biodiversity outcomes. The four scenarios we investigated are (1) sustainable increases in crop yields such that the yield gap, or the difference between current and maximum potential yields, was reduced by 80% by 2060; (2) a diet scenario where meat consumption is reduced in half and is instead replaced by an equivalent number of calories of dairy and eggs; (3) an international trade scenario, or where global trade from higher-yielding to lower-yielding nations is increased as a global land-sparing mechanism; and (4) a combined scenario, or where the yields, diet, and trade scenarios are simultaneously achieved. By 2060, the yield, diet, and trade scenario were projected to reduce cropland expansion in Sub-Saharan Africa by 195, 65, and 155 million hectares, respectively while simultaneous adoption of all three was projected to reduce 2060 cropland expansion by 290 million hectares (~64% of the size of the EU; Figure S4.

By 2060, the alternative scenarios were projected to prevent from ~15-48% of projected declines in remaining AOH compared to the Business-As-Usual scenario (Figure 5a). Net mean declines in remaining AOH in the alternative scenarios ranged from ~15.1 – 24.6% (Figure 5b), compared to a 28.9% mean decline in remaining AOH in the BAU scenario. The yields scenario is projected to have the largest benefit to biodiversity, avoiding ~47.7% of projected declines in remaining AOH compared to the BAU scenario. The trade scenario (~34.6% of projected AOH loss avoided) and diet scenario (~15.0% of projected AOH loss avoided) are projected to have smaller benefits to biodiversity, primarily because these scenarios were forecasted to reduce future agricultural expansion to a smaller extent than the yield scenario.

Simultaneously adopting the yield, trade, and diet scenarios could offer substantial benefits to biodiversity. The combined scenario was projected to avoid >80% of the declines in remaining AOH relative to the BAU scenario (Figure 5a). In addition, compared to the BAU scenario, ~67% fewer species would lose >10% of their remaining

AOH; ~91% fewer species would lose >25% of their remaining AOH; and ~95% fewer species would lose >50% of their remaining AOH. Biodiversity benefits in the combined scenario are projected to occur across nearly all of Sub-Saharan Africa, although benefits are projected to be largest in Southern Africa and Madagascar, and to a lesser extent along the eastern coast (Figure 4). Avoided declines in remaining AOH are projected to be smaller across northern Sub-Saharan Africa, largely because the land-sparing benefits of increasing crop yields is small in this region compared to other regions (**Figure S4**).

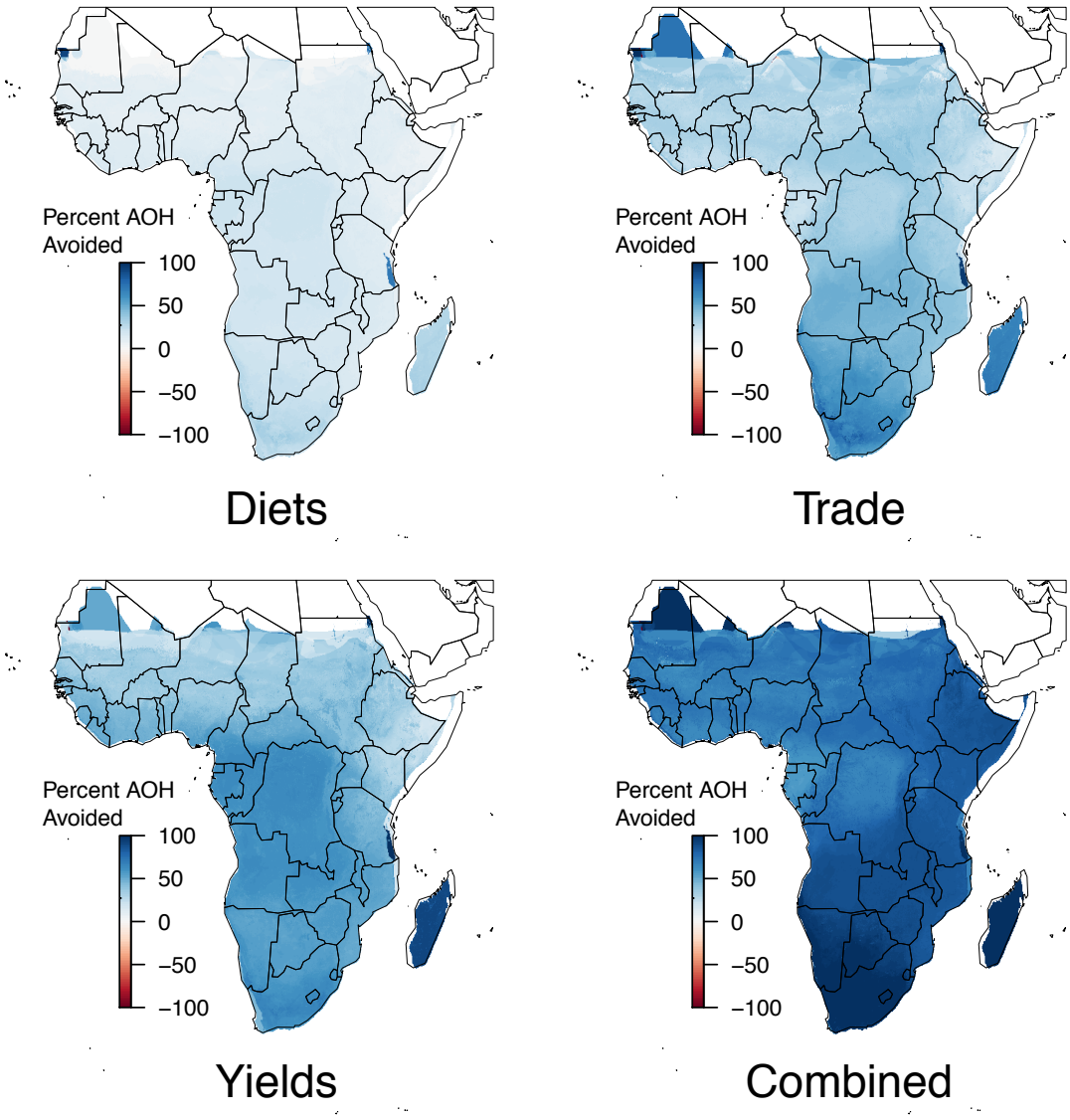

Figure 4. Percent of projected declines in AOH avoided in the diets, trade, yields, and combined scenarios. Percent of projected declines in AOH avoided was calculated across all species that historically existed in each cell. 100% indicates that all of the declines in remaining AOH would be avoided by adoption of the alternative scenarios; values <0% indicate that declines in remaining AOH are projected to be larger in the alternative scenario than in the BAU scenario.

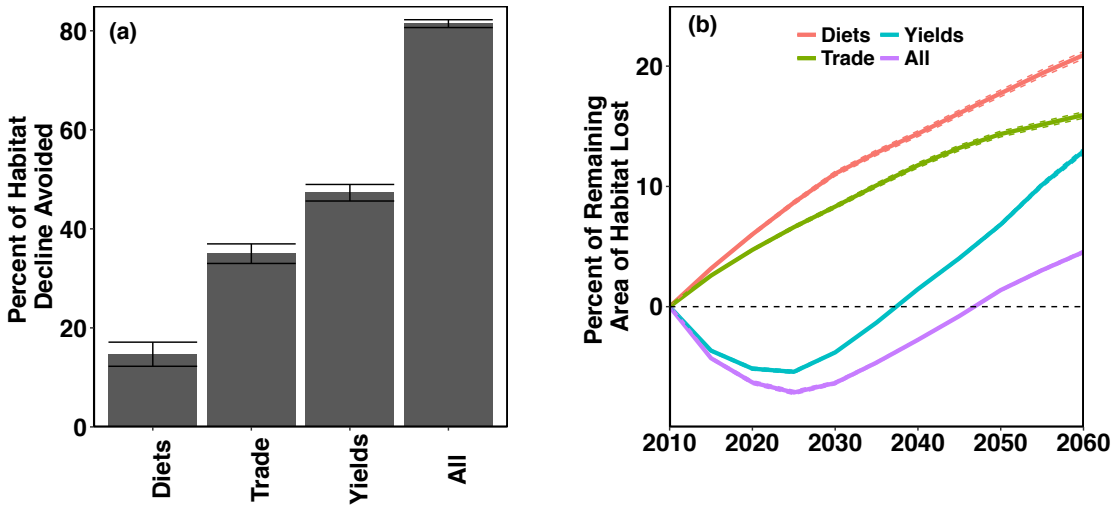

Figure 5. (a) Biodiversity savings relative to the BAU scenario and (b) declines in remaining area of habitat in the alternative scenarios. (a) Percent of projected area of remaining habitat lost that could be avoided in 2060 in the alternate scenarios relative to the BAU scenario. **(b)** Projected declines in remaining area of habitat across all species for the alternate scenarios. Bars in (a) and dashed lines in panel (b) represent +- 1 standard error.

Ensuring biodiversity in a world with growing food demand

If current trends continue, our projections suggest that agricultural expansion will decrease remaining area of habitat for birds in Sub-Saharan Africa by ~28.9% by 2060, with larger projected declines among species currently classified as "Critically Endangered", "Endangered", or "Vulnerable" by the IUCN. However, our yield, diet, and trade scenarios suggest that ~15– 48% of projected decreases in remaining AOH could be avoided, while our combined scenario suggests that >80% of the projected decreases in

remaining AOH could be avoided if closing yield gaps, shifting diets, and changing trade patterns to preferentially produce crops in higher-yield regions occurs simultaneously. These results strongly suggest that careful planning and prompt action to implement proactive approaches to reduce future agricultural land expansion might have the potential to avoid widespread biodiversity declines across Sub-Saharan Africa. This methodology, if applied to other regions and species types (e.g. mammals and amphibians), could be useful in guiding conservation efforts in regions where agricultural expansion is projected to have a large impact on biodiversity (e.g. South and Southeast Asia) (Tilman et al., 2017), that are highly diverse (e.g. Latin America and South and Southeast Asia) (IUCN, 2017), or that account for a large portion of current global biodiversity declines (e.g. United States and Australia; Rodrigues et al., 2014).

Our alternative scenarios demonstrate the potential benefits to biodiversity of reducing agricultural land expansion in Sub-Saharan Africa. However, maximizing effectiveness of reducing agricultural expansion will require additional land-use and economic planning (Angelsen, 2010; Ewers et al., 2009; Phalan et al., 2016). In addition, hunting; habitat loss driven by logging, mining, and energy development; pollution; altered fire and hydrological dynamics; and invasive species are also serious threats to biodiversity, while climate change is likely to increasingly threaten biodiversity in coming decades (IUCN, 2017; Mawell et al., 2016). These threats must be tackled with specific interventions such as increases in protected areas; more effective governance of hunting and other natural resource use; and tighter regulation of pollution. Doing so will require large increases in conservation efforts (Butchart et al., 2015; McCarthy et al., 2012) and risk imposing large opportunity costs on local people such as potential reductions in income, bushmeat consumption, and food security (Cawthorn & Hoffman, 2015). However, achieving our alternative scenarios could reduce these opportunity costs by reducing the need for wild protein sources and by providing sufficient food from land outside protected areas (e.g. by increasing crop production by closing yield gaps) (Foley et al., 2011).

We show that agricultural expansion in the coming decades has the potential to endanger bird diversity across Sub-Saharan Africa. Swift implementation of economically, politically, socially, and culturally appropriate policies to reduce future agricultural land demand by increasing crop yields (e.g. Cui et al., 2018; Dorward et al., 2011; Druilhe & Barreiro-hurlé, 2012; Godfray & Garnett, 2014; Robertson et al., 2014), shifting diets (e.g. Cochero et al., 2017; Thorndike et al., 2014; Vallgårda et al., 2015), or changing the location of agricultural production (e.g. Polasky et al., 2005) could avoid much of the projected declines in remaining area of habitat. Swift implementation of these, and other, policies will be a huge challenge, but one which cannot be avoided if the avian biodiversity of Sub-Saharan Africa is to be safeguarded for future generations.

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Appendix.

Supporting Information

Chapter 2:

Table S1. Publications included in the LCA meta-analysis of Chapter 2.

Table S1

Author	Year	Location of Study (where possible)	Food Groups	Journal
Abeliotis	2012	Greece	Legumes	Journal of Cleaner Production
Aguilera	2015a	Spain	Rice	Agronomic Sustainable Development
Aguilera	2015b	Spain	Temperate Fruits	Agronomic Sustainable Development
Alaphilippe	2013	France	Temperate Fruits	Agronomic Sustainable Development
Arsenault	2008	Canada	Milk and Yogurt	International Journal of Agricultural Sustainability
Aubin	2009	Greece	Non-Recirculating Aquaculture, Recirculating Aquaculture	Journal of Cleaner Production
Avraamides	2006	Cyprus	Oils	Journal of Cleaner Production
Ayer	2009	Canada	Non-Recirculating Aquaculture, Recirculating Aquaculture	Journal of Cleaner Production
Basset-Mens	2005	France	Pork	Agriculture, Ecosystems and Environment
Basset-Mens	2009	New Zealand	Milk and Yogurt	Ecological Economics
Beauchemin	2010	Canada	Beef	Animal Feed Science and Technology
Bengtsson	2013	Australia	Poultry	Journal of Cleaner Production
Berlin	2002	Sweden	Cheese	International Dairy Journal
Biswas	2008	Australia	Wheat	Water and Environment Journal
Biswas	2010	Australia	Mutton and Goat, Wheat	Journal of Cleaner Production
Blengini	2009	Italy	Rice	Journal of Environmental Management
Blonk	2009	Netherlands, Denmark, England, Germany	Pork	Wageningen University
Bosch	2010	Spain	Mutton and Goat	Options Méditerranéennes : Série A. Séminaires Méditerranéens;
Bosma	2011	Vietnam	Non-Recirculating Aquaculture	International Journal of Life Cycle Assessment
Brentrup	2003	England	Wheat	European Journal of Agronomy
Brodt	2014	California	Rice	Field Crops Research
Buchspies	2011	Denmark	Non-Recirculating Aquaculture, Trawling Fishery	ESU-Services
Canals	2006	New Zealand	Temperate Fruits	Agriculture, Ecosystems and Environment
Cao	2011	China	Non-Recirculating Aquaculture	Environmental Science and Technology
Casey	2005	Ireland	Beef, Milk and Yogurt, Mutton and Goat	The Society for Engineering in Agricultural, Food, and Biological Systems
Casey	2006	Ireland	Beef	Agricultural Systems
Cederberg	2000	Sweden	Milk and Yogurt	Journal of Cleaner Production
Cederberg	2004	Sweden	Milk and Yogurt	Swedish Institute for Food and Biotechnology
Cederberg	2009	Sweden	Beef, Eggs, Milk and Yogurt, Pork, Poultry	Swedish Institute for Food and Biotechnology
Cellura	2012	Italy	Greenhouse Temperate Fruits, Greenhouse Vegetables	Journal of Cleaner Production
Cerutti	2013	Italy	Temperate Fruits	Journal of Cleaner Production
Charles	2006	Switzerland	Wheat	Agriculture, Ecosystems and Environment
Cherubini	2015	Brazil	Pork	Journal of Cleaner Production
Choo	2011	Malaysia	Oil Crops	International Journal of Life Cycle Assessment
Clarke	2013	Ireland	Beef	Journal of Agricultural Science
d'Orbcastel	2009	France	Non-Recirculating Aquaculture, Recirculating Aquaculture	Aquacultural Engineering
da Silva	2010	Brazil	Legumes	Journal of Environmental Management
Daneshi	2014	Iran	Milk and Yogurt	Journal of Cleaner Production
de Backer	2008	Europe	Vegetables	British Food Journal
Dekker	2011	Netherlands	Eggs	Livestock Science
Dekker	2013	Netherlands	Eggs	Livestock Science
deLeis	2013	Brazil	Milk and Yogurt	International Journal of Life Cycle Assessment
Devers	2011	South Africa, Belgium	Pork	Agrekon
Dick	2015	Brazil	Beef	Journal of Cleaner Production
Djekic	2014	Serbia	Butter/Cream, Milk and Yogurt	Journal of Cleaner Production
Driscoll	2010	United States	Non-Trawlinging Fishery, Trawling Fishery	Marine Policy
Dwivedi	2012	United States	Tropical Fruits	Agricultural Systems
Edward-Jones	2009	Wales	Beef, Mutton and Goat	Journal of Agricultural Science
Ellingsen	2009	Norway	Non-Recirculating Aquaculture	Marine Policy
Eriksson	2005	Sweden	Pork	International Journal of Life Cycle Assessment
Fallahpour	2012	Iran	Other Cereals, Wheat	Environment, Development and Sustainability
Flachowsky	2009		Beef	Journal of Consumer Protection and Food Safety
Foley	2011	Ireland	Beef	Agriculture, Ecosystems and Environment
Fusi	2014	Italy	Rice	Science of the Total Environment
Gazulla	2010	Spain	Temperate Fruits	International Journal of Life Cycle Assessment
Girgenti	2013	Italy	Temperate Fruits	Science of the Total Environment
Gonzalez Garcia	2014	Portugal	Poultry	Journal of Cleaner Production
Gonzalez-Garcia	2013	Portugal	Cheese, Milk and Yogurt	International Journal of Life Cycle Assessment
Graefe	2013	Colombia	Tropical Fruits	Fruits
Gronroos	2006	Finland	Non-Recirculating Aquaculture	Boreal Environment Research
Guerci	2013	Denmark, Germany, Italy	Milk and Yogurt	Journal of Cleaner Production
Gunady	2012	Australia	Temperate Fruits, Vegetables	Journal of Cleaner Production
Haas	2001	Germany	Milk and Yogurt	Agriculture, Ecosystems and Environment
Halberg	2010	Denmark	Pork	Agronomic Sustainable Development
Henricksson	2014	Sweden	Milk and Yogurt	Animal
Hokazono	2012	Japan	Rice	Journal of Cleaner Production
Hortenhuber	2010	Austria	Milk and Yogurt	Renewable Agriculture and Food Systems
Hospido	2005	Spain	Non-Trawlinging Fishery	Fisheries Research
Hospido	2008	UK, Spain	Vegetables	International Journal of Life Cycle Assessment
Ingwersen	2012	Costa Rica	Tropical Fruits	Journal of Cleaner Production
Iriarte	2014	Ecuador	Tropical Fruits	Science of the Total Environment

Table S1 Cont.

Author	Year	Location of Study (where possible)	Food Groups	Journal
Iribarren	2010	Spain	Non-Recirculating Aquaculture, Non-Trawlinging Fishery, Trawling Fishery	Science of the Total Environment
Jerbi	2012	Africa	Non-Recirculating Aquaculture	
Kendall	2012	United States	Tree Nuts	Almond Board of California
Khoshnevisan	2014	Iran	Rice	Science of the Total Environment
Khoshnevisan	2013	Iran	Greenhouse Temperate Fruits, Temperate Fruits	European Journal of Agronomy
Kim	2008	United States	Maize	International Journal of Life Cycle Assessment
Kim	2013	United States	Cheese	International Journal of Life Cycle Assessment
Knudsen	2010	China	Legumes	Journal of Cleaner Production
Koroneos	2005	Greece	Alcohol	Journal of Cleaner Production
Leinonen	2013	United Kingdom	Eggs, Poultry	Agricultural Systems
Leinonen	2012a	United Kingdom	Eggs	Poultry Science Association
Leinonen	2012b	United Kingdom	Poultry	Poultry Science Association
Leng	2008	China	Roots	Journal of Cleaner Production
Lindelauf	2009	Germany	Milk and Yogurt	Livestock Science
Liu	2010	China	Temperate Fruits	Journal of Cleaner Production
Lovett	2008	Ireland	Milk and Yogurt	Livestock Science
Maciel	2015	Brazil	Legumes	Journal of Cleaner Production
Martinez-Blanco	2011	Spain	Greenhouse Vegetables, Vegetables	Journal of Cleaner Production
Mellenhorst	2006	Netherlands	Eggs	British Poultry Science
Michos	2008	Greece	Temperate Fruits	Ecological Indicators
Moudry	2013	Czech Republic	Wheat	Journal of Food, Agriculture, and Environment
Mouron	2006	Switzerland	Temperate Fruits	Agriculture, Ecosystems and Environment
Neto	2013	Portugal	Alcohol	International Journal of Life Cycle Assessment
Nguyen	2010	Europe	Pork	Journal of Cleaner Production
Nguyen	2012	France	Beef	Journal of Agricultural Science
Nilsson	2012	UK, Germany, France	Butter/Cream	International Journal of Life Cycle Assessment
O'brien	2012	Ireland	Milk and Yogurt	Agricultural Systems
O'brien	2014a	Ireland	Milk and Yogurt	Journal of Dairy Science
O'brien	2014b	Ireland	Milk and Yogurt	International Journal of Life Cycle Assessment
Ogino	2013	Japan	Pork	Soil Science and Plant Nutrition
Olesen	2006	Europe	Milk and Yogurt	Agriculture, Ecosystems and Environment
Page	2011	New Zealand	Temperate Fruits, Tropical Fruits	HortScience
Page	2012	Australia	Greenhouse Vegetables, Vegetables	Journal of Cleaner Production
Pattara	2012	United States, Europe, South Africa	Alcohol	Environmental Management
Payen	2015	Morocco	Greenhouse Vegetables	Journal of Cleaner Production
Pelletier	2009	Norway, UK, Canada, Chile	Non-Recirculating Aquaculture	Environmental Science and Technology
Pelletier	2013	United States	Eggs	Journal of Cleaner Production
Pelletier	2008a	Canada	Legumes, Maize, Oil Crops, Wheat	Environmental Management
Pelletier	2008b	Canada	Poultry	Agricultural Systems
Pelletier	2010a	United States	Beef	Agricultural Systems
Pelletier	2010b	United States	Pork	Agricultural Systems
Pelletier	2010c	Indonesia	Non-Recirculating Aquaculture, Recirculating Aquaculture	Journal of Industrial Ecology
Pergola	2013	Italy	Tropical Fruits	Journal of Environmental Management
Peters	2010	Australia	Beef	Environmental Science and Technology
Phetteplace	2001	United States	Beef, Milk and Yogurt	Nutrient Cycling in Agroecosystems
Phong	2011	Vietnam	Non-Recirculating Aquaculture	Livestock Science
Pirlo	2014	Italy	Buffalo Milk	Journal of Dairy Science
Pishgar-Komleh	2012	Iran	Roots	Journal of Cleaner Production
Point	2012	Canada	Alcohol	Journal of Cleaner Production
Rajaeifar	2014	Iran	Oils	Energy
Ramjeawon	2004	Mauritius	Sugar	International Journal of Life Cycle Assessment
Ramos	2011	Spain	Non-Trawlinging Fishery, Trawling Fishery	International Journal of Life Cycle Assessment
Raucci	2015	Brazil	Legumes	Journal of Cleaner Production
Reckmann	2013	Germany	Pork	Livestock Science
Ridoutt	2013	Australia	Wheat	Agricultural Systems
Roer	2011	Norway	Other Cereals, Wheat	Agricultural Systems
Roer	2013	Norway	Beef, Milk and Yogurt	Livestock Science
Romero Gamez	2014	Spain	Vegetables, Greenhouse Vegetables	Journal of Cleaner Production
Ross	2014	Scotland	Milk and Yogurt	Livestock Science
Samuel-Fitwi	2013		Non-Recirculating Aquaculture, Recirculating Aquaculture	Aquacultural Engineering
Saunders	2008	New Zealand, UK	Temperate Fruits, Vegetables	Political Science
Schau	2009	Norway	Non-Trawlinging Fishery	Journal of Cleaner Production
Schils	2005	Europe	Milk and Yogurt	Nutrient Cycling in Agroecosystems
Schmidt	2010	Malaysia	Oils	International Journal of Life Cycle Assessment
Schmidt	2015	Malaysia	Oils	Journal of Cleaner Production
Seabra	2012	Brazil	Sugar	Biofuels, Bioproducts, and Biorefining
Sheane	2011	Scotland	Butter/Cream, Cheese, Milk and Yogurt	Scottish Government
Shiina	2011	Japan	Greenhouse Vegetables	Proc. XXVIIIth IHC – IS on Engineering Modelling, Monitoring, Mechanization and Automation Tools for Precision Hort
Tamburini	2015	Italy	Temperate Fruits, Vegetables, Wheat	Sustainability
Thevenot	2013	Réunion	Poultry	Journal of Cleaner Production
Thoma	2013	United States	Milk and Yogurt	International Dairy Journal
Thomassen	2008	Netherlands	Milk and Yogurt	Agricultural Systems

Table S1 Cont.

Author	Year	Location of Study (where possible)	Food Groups	Journal
Thrane	2004	Denmark	Non-Trawlinging Fishery, Trawling Fishery	Journal of Industrial Ecology
Thrane	2006	Denmark	Trawling Fishery	Fisheries
Torellas	2012	Spain	Greenhouse Vegetables	International Journal of Life Cycle Assessment
Tuomisto	2012		Wheat	Annals of Applied Biology
Tyedmers	2001	Europe	Non-Trawlinging Fishery, Trawling Fishery	Fisheries Centre Research Report
Uchida	2012	Japan	Roots	Biomass and Bioenergy
van Middelaar	2013	Netherlands	Milk and Yogurt	Agricultural Systems
Vazquez-Rowe	2012	Spain	Temperate Fruits	Journal of Cleaner Production
Vazquez-Rowe	2011	Spain	Non-Trawlinging Fishery, Trawling Fishery	Fisheries Research
Vergé	2007	Canada	Milk and Yogurt	Agricultural Systems
Vergé	2008	Canada	Beef	Agricultural Systems
Vergé	2009	Canada	Eggs, Poultry	Journal of Applied Poultry Research
Wang	2009	China	Maize, Wheat	International Journal of Sustainable Development and World Ecology
Wang	2010	China	Rice	International Journal of Sustainable Development and World Ecology
Wang	2014	China	Maize, Wheat	Journal of Cleaner Production
Weiske	2005	Europe	Milk and Yogurt	Agriculture, Ecosystems and Environment
Wiedemann	2015	Australia	Beef, Mutton and Goat	Journal of Cleaner Production
Williams	2006	England	Beef, Eggs, Greenhouse Vegetables, Milk and Yogurt, Mutton and Goat, Oil Crops, Pork, Poultry, Roots, Wheat	
Yan	2013	Ireland	Milk and Yogurt	Journal of Dairy Science
Zafiriou	2012	Greece	Vegetables	Journal of Dairy Science
Ziegler	2003	Baltic Sea	Non-Trawlinging Fishery, Trawling Fishery	International Journal of Life Cycle Assessment

Table S2. Foods included in each food group for Figures 8 of Chapter 2 and Figure S1

Food Group	Food Items	N Data Points
Maize	Maize	13
Wheat	Wheat	37
Rice	Rice	13
Fresh Produce	Andean blackberry, Apples, Asparagus, avocado, Banana, Blueberries, Chicory, Chinese Pear, Escarole, golden berry, Grapes, Kiwis, Leeks, Lemons, Lettuce, lulo, mango, Mushrooms, Onions, Oranges, passion fruit, Peaches, Pear, Pineapple, Raspberries, Romaine Lettuce, Strawberries, Tomatoes, tree tomato	74
Eggs	Eggs	64
Dairy	Milk, Yogurt	124
Poultry	Chicken	36
Pork	Pork	41
Non-Trawling Fisheries	Cod, Crab, Eel, Flat fish, herring, Mackerel, Mussels, Pollock, Sea-bass, Snapper, Swordfish, Tuna, Turbot	77
Trawl Fishery	Anglerfish, Cod, Crab, Flat fish, Herring, Mackerel, Pollock, Snapper, Squid	34
Non-Recirculating Aquaculture	Catfish, Mussels, Salmon, Sea-bass, Shrimp, Tilapia, Trout	25
Recirculating Aquaculture	Char, Trout, Turbot	5
Ruminant Meat	Beef, Mutton, Goat	74

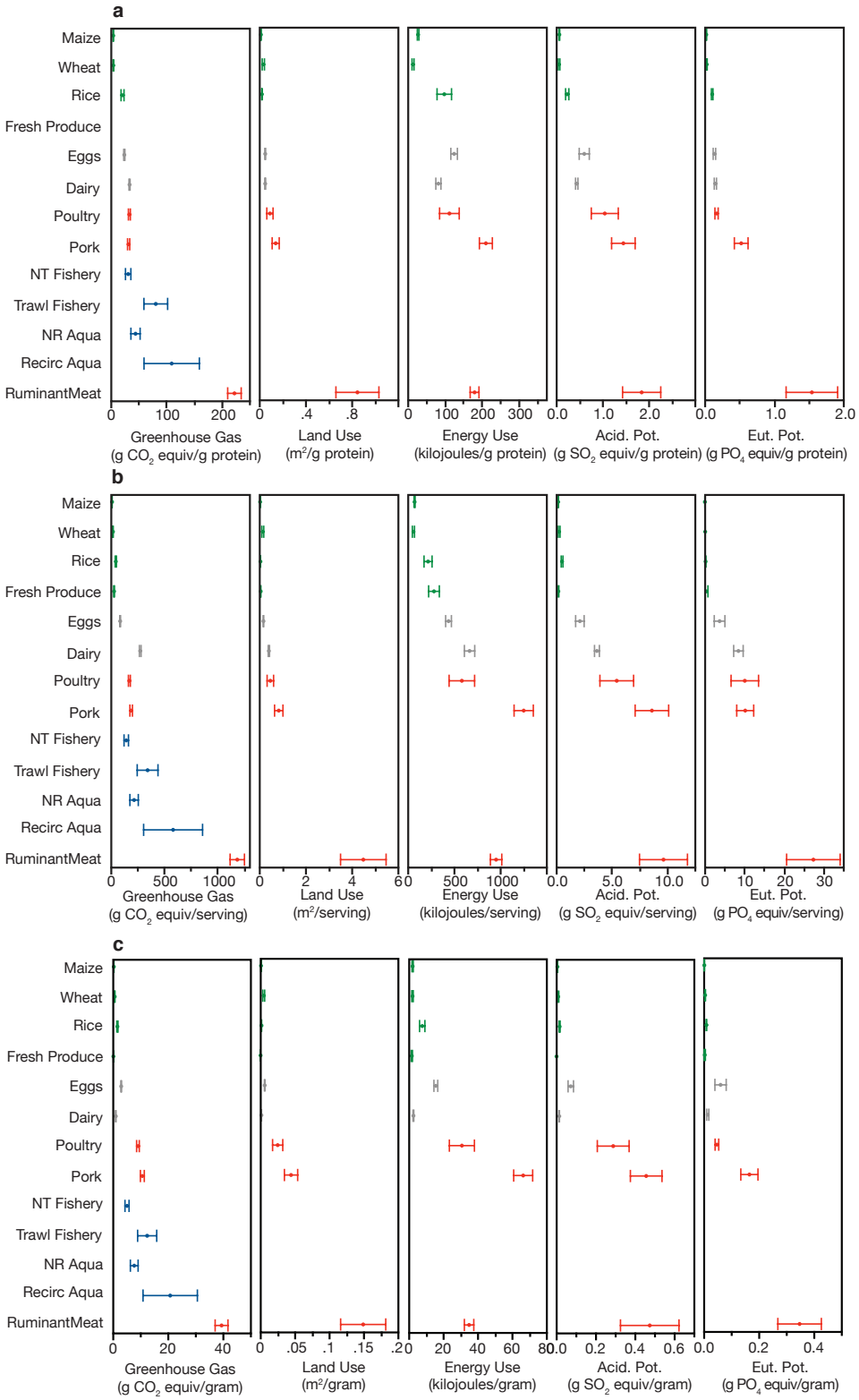

a
Maize
Wheat
Rice
Fresh Produce
Eggs
Dairy
Poultry
Pork
NT Fishery
Trawl Fishery
NR Aqua
Recirc Aqua
RuminantMeat
0 100 200
Greenhouse Gas
(g CO2 equiv/g protein)
0 .4 .8
Land Use
(m2/g protein)
0 100 200 300
Energy Use
(kilojoules/g protein)
0.0 1.0 2.0
Acid. Pot.
(g SO2 equiv/g protein)
0.0 1.0 2.0
Eut. Pot.
(g PO4 equiv/g protein)
b
0 500 1000
Greenhouse Gas
(g CO2 equiv/serving)
0 2 4 6
Land Use
(m2/serving)
0 500 1000
Energy Use
(kilojoules/serving)
0.0 5.0 10.0
Acid. Pot.
(g SO2 equiv/serving)
0 10 20 30
Eut. Pot.
(g PO4 equiv/serving)
c
0 20 40
Greenhouse Gas
(g CO2 equiv/gram)
0 .05 .1 .15 .20
Land Use
(m2/gram)
0 20 40 60 80
Energy Use
(kilojoules/gram)
0.0 0.2 0.4 0.6
Acid. Pot.
(g SO2 equiv/gram)
0.0 0.2 0.4
Eut. Pot.
(g PO4 equiv/gram)

Figure S1. Environmental impacts of broad food groups per gram protein **(a)**,USDA serving **(b)**, and gram **(c)**. Bars show mean and standard errors. Plant-based foods are in green; dairy and eggs are in grey; meats are in red; and seafood is in blue. Data from foods grown in greenhouses are not included when plotting this figure. Trawl Fishery = bottom-trawling fisheries; NT Fishery = all other fisheries (e.g. line, purse net, seine net, etc); Recirc Aqua = recirculating aquaculture; NR Aqua = non-recirculating aquaculture (e.g. pond, net pen, flow-through, etc). The impacts of producing fresh produce per gram protein are not shown because these foods are not consumed for their protein content.

Chapter 3:

Supporting Information

Description of dose-response meta-analyses:

Prospective cohort studies follow populations through time as a way to examine the health outcomes of different dietary patterns. Prospective cohort studies report health outcomes in one of three ways: 1) dose-response; 2) comparing quintiles; or 3) substitution. Dose-response studies report the health impact of consuming a serving of food per day, for example the health impact of consuming a first additional serving of red meat per day. Studies comparing quintiles report the health impact of extreme quintiles of food consumption, for example the health outcome of the subgroup that consumes the least added sugar against the health outcome of the subgroup that consumes the most added sugar. Studies examining food substitution report the health outcome of substituting one food for another, for example the health outcome of substituting one serving of red meat for an equivalent amount of chicken meat per day.

Dose-response meta-analyses analyses were used in our analyses for several reasons. First, they allow for more direct comparison of the health and environmental outcome of different foods. For instance, the serving sizes reported in dose-response meta-analyses vary from 20 – 200g per day and are similar in size to what is consumed at a meal. In addition, there are dose-response meta-analyses for most commonly consumed food groups. In total, we collected data from 23 dose-response meta-analyses that examined

the marginal health impact of consuming an additional serving of food per day for 13 (**Supplemental Table 1; Figure S1**).

Dose-response meta-analyses control for confounding variables when reporting the health outcomes of food consumption. Age, sex, history of smoking, race, and economic status are commonly controlled for in meta-analyses because they are known to influence health outcomes. Many dose-response meta-analyses report the health outcomes when controlling for different sets of confounding variables. When more than one health outcome was reported in a meta-analyses, the health outcome that controlled for the largest number of confounding variables was used here because this reduces the potential that uncontrolled for confounding variables are driving the observed health outcomes of food consumption. Further, we chose the dose-response meta-analysis that was most recently published when there were multiple dose-response meta-analyses examining the same food. Dose-response meta-analyses that were funded in part by industry were not included in this analysis because of potential biases.

The underlying health data shows that additional consumption of many of the foods examined here reduces disease risk. However, these foods should not be consumed in excess quantities and should instead be consumed as part of a balanced diet. Excess caloric consumption and resultant weight gain lead to negative health outcomes (Whitlock et al., 2009); simply eating more of a healthy food without decreasing consumption of a different food may not be beneficial to health.

Many of the health meta-analyses included in these analyses examine populations that are primarily Caucasian. However, the health impact of food consumption can differ depending on food preparation method (Wallin et al., 2012), between individuals without and with pre-existing diseases (Rong et al., 2013), or between individuals that have different baseline dietary habits (e.g. ref Aune et al., 2016b). For example, diabetes incidence is higher in men than women in Chinese, South Asian, and white populations (Khan et al., 2011), whereas African Americans are more predisposed for many cancers

than are Hispanics, Asian Americans, and Caucasians (Siegel et al., 2017). Using analyses that examined non-Caucasian populations may affect the results presented here.

Description of Life Cycle Assessments:

Life Cycle Assessments:

Life cycle assessments (LCAs) are a standardized and internationally recognized method to estimate the environmental impacts per unit of food production. The meta-analysis of LCAs from which estimates of greenhouse gas emissions, land use, eutrophication potential (a measure of nutrient runoff) per gram of food were obtained estimated the environmental impacts from cradle-to-farm gate. This system boundary accounts for all impacts that occur from pre-farm and on-farm activities. As such, activities such as fertilizer production and application, infrastructure construction, and on-farm fossil fuel use are included in these estimates. Post-farm activities such as transportation, processing, refrigeration, and cooking are not included in the analysis because of the few number of studies that report impacts from these activities. Including these activities would likely not have a large impact on the results reported here. Irrigation water use was obtained from an analysis that used LCA-like methodology.

The LCA publications included in the meta-analysis are largely based on Westernized and highly mechanized agricultural systems. However, production systems can differ in their environmental impact across geographical regions based on their production methodology and access to fertilizer inputs (Carlson et al., 2016; Herrero et al., 2013). Estimates of the environmental impact of food production in less-affluent and non-westernized production system exist; these analyses show similar trends in the environmental impacts of food production as LCAs. That is, minimally processed plant-based foods have low environmental impacts; dairy, chicken, and eggs have intermediate environmental impacts; and ruminant meat has high environmental impacts (Carlson et al., 2016; Herrero et al., 2013). Using estimates of the environmental impacts of food production from less affluent nations would therefore likely change the absolute

magnitude of the impacts used here, but would likely not have a large impact on the relative magnitude of environmental impacts reported here.

Agricultural production method can also be a determinant of a food's environmental impact. Organic systems, for example, often require more land and cause more eutrophication per unit of food produced than non-organic systems (Clark & Tilman, 2017; Seufert & Ramankutty, 2017) while agricultural systems in developing nations can have environmental impacts an order of magnitude or more larger than those in developed nations because of differences in access to agricultural inputs (e.g. fertilizer and improved seeds; Carlson et al., 2016; Herrero et al., 2013). To best control for these differences, we used estimates of the environmental impact of food production from non-organic systems in developed nations.

Environmental impacts of fish

The environmental impact of fish production is highly dependent on production methodology. Trawling fisheries emit ~3x more GHGs than other types of fisheries while recirculating aquaculture emits ~3x more GHGs than non-recirculating aquaculture. Further, while production of wild-caught fish requires no land, uses no irrigation water, and results in very small amounts of eutrophication, production of fish in aquaculture systems requires land, can use irrigation water, and results in larger amounts of eutrophication.

Because of the differences in the environmental impact of fish production, we estimated the environmental impact per serving of fish by first assuming that half of fish production is from wild-caught fisheries and half is from aquacultural systems (which is approximately equivalent to the current proportions of fish production; FAO, 2016). We then assumed that half of wild-caught fish are produced via bottom trawling and half is produced using other capture methodologies. Because the LCA meta-analysis did not report estimates of land use, irrigation water use, or eutrophication, we then estimated the land use, irrigation water use, and eutrophication impact per serving of aquaculture fish

produced using the feed conversion ratios and fish feed composition reported in Tilman and Clark (2014) and the land use, irrigation water use, and eutrophication impact estimates used elsewhere in this analysis.

Calculating total mortality from disease-specific endpoints

We estimated incidence of total mortality for nuts, SSBs, and eggs using the relative risk of disease for disease-specific endpoints. To do so, we weighted the RR for each disease for which we had data for that food group by the contribution of that disease to global mortality. For instance, if the RR for CHD is 1.1, the RR for stroke is 1.2, and the RR for diabetes is 1, and the relative contribution of CHD, stroke, and diabetes to global mortality is 0.5 (e.g. 50% of mortality from these three disease-specific endpoints), 0.4, and 0.1, respectively, our estimate of total mortality for that food would be 1.13 (1.1 * 0.5 + 1.2 * 0.4 + 1 * 0.1). The upper and lower confidence intervals for total moratlity for nuts, SSBs, and eggs were calculated in the same way, except using the upper and lower confidence intervals reported for disease-specific endpoints.

Calculating the average relative risk of disease

In Figure 3, we report the average relative risk of disease. To calculate this, we averaged the reported relative risk of disease across all four disease endpoints included in this analysis. For example, if a food has a relative risk of disease of 0.9 for mortality, 0.95 for CHD, 0.8 for diabetes, and 0.85 for stroke, that food's averaged relative risk of disease would be 0.875 ([0.9 + 0.95 + 0.8 + 0.85]/4)

Calculating the average relative environmental impact

Because the absolute magnitude of the environmental impact of food production varies across environmental indicators, we reported the environmental impact in this analysis as the environmental impact relative to a serving of vegetables (which have the lowest environmental impact across all indicators examined). As such, a relative environmental impact of 1 indicates that a food has the same impact as vegetables, a relative environmental of 0.5 indicates that a food has half the environmental impact of

vegetables, while a relative environmental impact of 2 indicates that a food has twice the environmental impact of vegetables.

To examine the average relative environmental impact of food production, we averaged the relative environmental impact of a food across all four environmental indicators examined here. For example, if a food has a relative environmental impact of 2 for GHGs, 3 for land, 10 for eutrophication, and 5 for water, the averaged relative environmental impact of that food would be 5 ([2 + 3 + 10 + 5] / 4).

Supplemental Figures

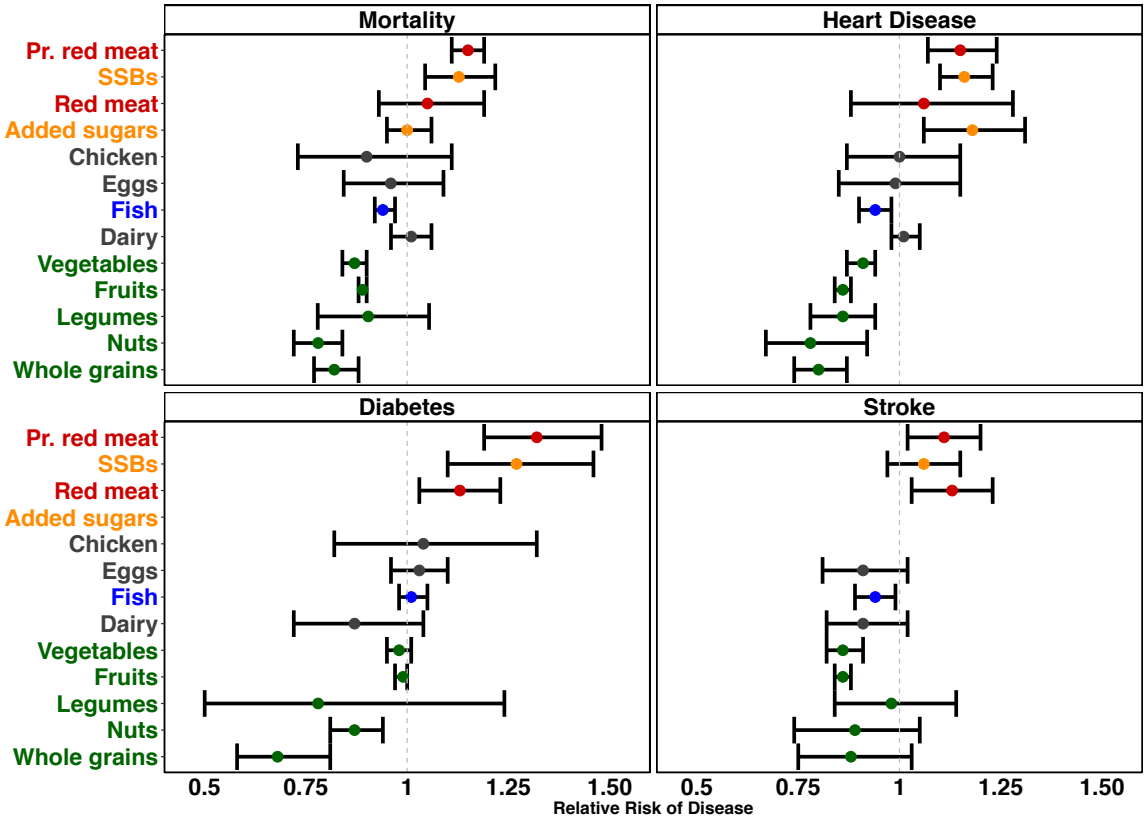


Figure S1. Relative risk of disease per additional serving of food consumed per day, where a relative risk > 1 indicates that a food is associated with increased disease risk and a relative risk < 1 indicates that a food is associated with decreased disease risk. Food groups are ordered from least healthy (top; largest average relative risk) to most healthy

(bottom; lowest average relative risk) and are colored where red = red meat; orange = sugars; grey = chicken, dairy, and eggs; blue = fish; and green = minimally processed plant-based foods. Data shows mean relative risk and 95% confidence intervals. Publications included in this analysis can be found in Table S1.

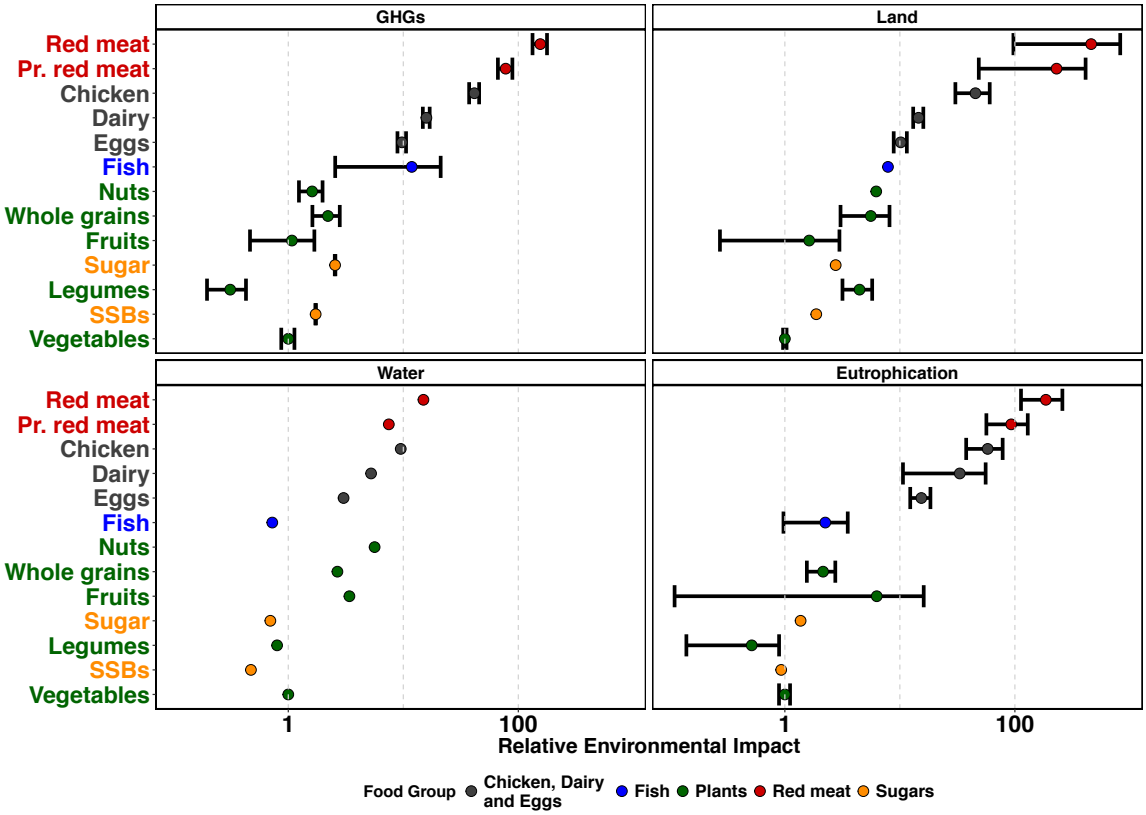


Figure S2. Relative environmental impact per serving of food produced relative to the impact of a serving of vegetables. Food groups are ordered from highest impact (top; largest average relative environmental impact) to lowest impact (bottom; lowest average relative environmental impact) and are colored where red = red meat; orange = sugars; grey = chicken, dairy, and eggs; blue = fish; and green = minimally processed plant-based foods. Data for GHGs is from Clark & Tilman, (2017); Clune et al., (2017); data for land is from Clark & Tilman, (2017; FAO, (2017); data for blue water use is from

Mekonnen & Hoekstra, (2010); and data for eutrophication is from Clark & Tilman, (2017)**.** Error bars indicate +- standard deviation; missing error bars indicate that the underlying data source did not provide estimates of error.

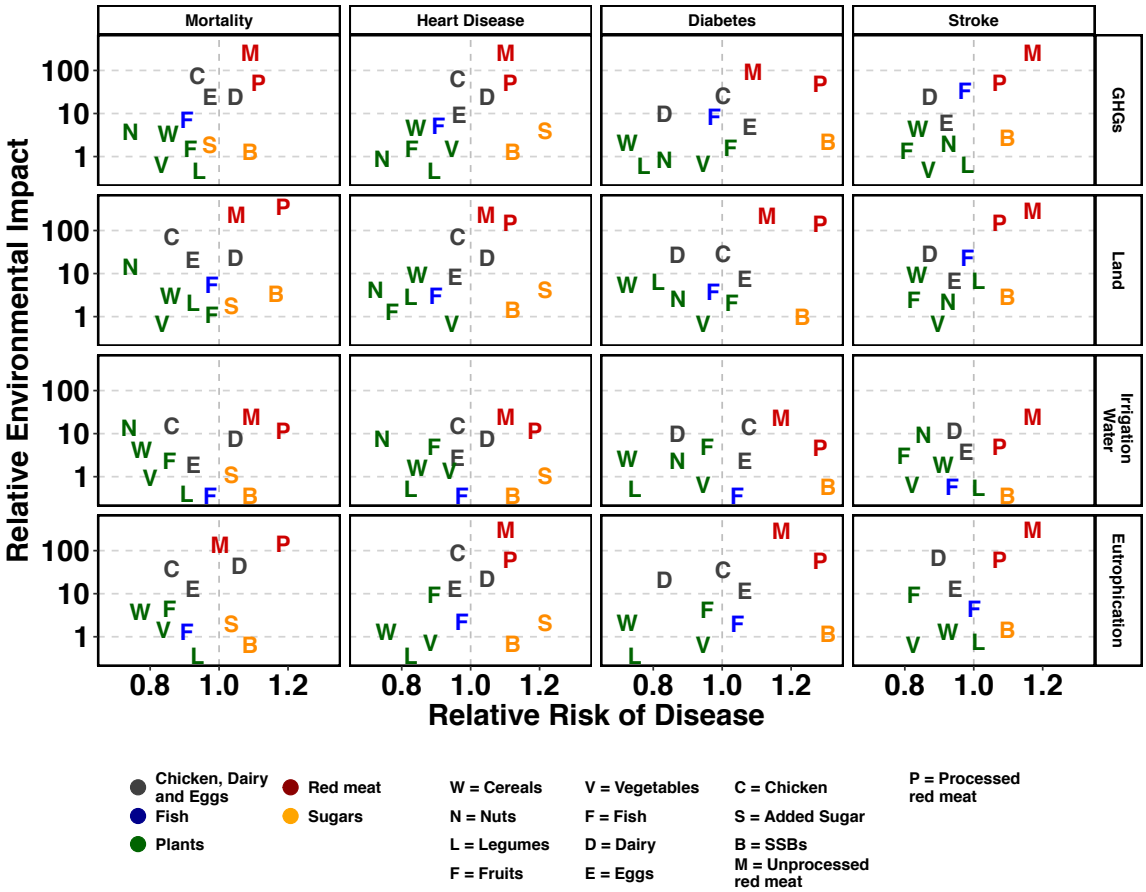


Figure S3. Association between the health and environmental impact of 13 food groups for four health endpoints and four environmental indicators. Letters denote food type, are jittered to avoid overlap, and are colored where green = minimally processed plant-based foods; blue = fish; grey = chicken, dairy, and eggs; red = red meats; and orange = sugars. The health impact is reported as the relative risk of disease per serving of food consumed per day, where a relative risk > 1 indicates that a food is associated with increased disease risk and a relative risk < 1 indicates that a food is

associated with decreased disease risk. The relative environmental impact is reported as the environmental impact relative to a serving of vegetables.

Supplemental Tables

Lead Author	Year Published	Journal	Food Examined
Larsson	2011	Stroke	Fish
Wallin	2012	Diabetes Care	Fish
Zheng	2012	Public Health Nutrition	Fish
Aune	2013	AJCN	Dairy
Aune	2013	European Journal of Epidemiology	Whole grains
Chen	2013	EJCN	Unprocessed red meat; processed red meat
Feskens	2013	Current Diabetes Reports	Chicken; unprocessed red meat; processed red meat
Rong	2013	BMJ	Eggs
Wallin	2013	Diabetologia	Eggs
Abete	2014	Journal of Nutrition	White meat
Afshin	2014	AJCN	Legumes; nuts
Huang	2014	Atherosclerosis	SSBs
Taveska	2014	AJCN	Sugar
Yang	2014	JAMA	Sugar
Imamura	2015	BMJ	SSBs
Wang	2015	Public Health Nutrition	Unprocessed red meat; processed red meat
Wu	2015	Nutrition, Metabolism & Cardiovascular Diseases	Fruits; vegetables
Xi	2015	British Journal of Nutrition	SSBs
Zhao	2015	European Journal of Clinical Nutrition	Fish
Aune	2016	BMC Medicine	Total nuts
Aune	2016	BMJ	Whole grains
Mullie	2016	BMC Public Health	Dairy
Aune	2017	International Journal of Epidemiology	Fruits; vegetables

Table S1. Dose-response health meta-analyses included in Chapter 3.

Food Group	Disease Endpoint	Serving size (g)	Environmental Indicator	Relative Risk of Disease	Environmental Impact per serving of food	Relative Environmental Impact per serving of food (baseline = vegetables)
Chicken	Diabetes	100	Eutrophication (g PO4)	1.04	4.49	55.78
Chicken	Diabetes	100	GHGs (g CO2-e)	1.04	575.24	39.89
Chicken	Diabetes	100	Irrigation Water (Liters)	1.04	31300	9.13
Chicken	Diabetes	100	Land (m^2)	1.04	0.89	43.65
Chicken	Heart Disease	100	Eutrophication (g PO4)	1	4.49	59.12
Chicken	Heart Disease	100	GHGs (g CO2-e)	1	575.24	42.29
Chicken	Heart Disease	100	Irrigation Water (Liters)	1	31300	9.68
Chicken	Heart Disease	100	Land (m^2)	1	0.89	46.27
Chicken	Mortality	100	Eutrophication (g PO4)	0.9	4.49	59.12
Chicken	Mortality	100	GHGs (g CO2-e)	0.9	575.24	42.29
Chicken	Mortality	100	Irrigation Water (Liters)	0.9	31300	9.68
Chicken	Mortality	100	Land (m^2)	0.9	0.89	46.27
Dairy	Diabetes	200	Eutrophication (g PO4)	0.87	2.55	31.74
Dairy	Diabetes	200	GHGs (g CO2-e)	0.87	218.98	15.19
Dairy	Diabetes	200	Irrigation Water (Liters)	0.87	17200	5.02
Dairy	Diabetes	200	Land (m^2)	0.87	0.28	13.9
Dairy	Heart Disease	200	Eutrophication (g PO4)	1.01	2.55	33.64
Dairy	Heart Disease	200	GHGs (g CO2-e)	1.01	218.98	16.1
Dairy	Heart Disease	200	Irrigation Water (Liters)	1.01	17200	5.32
Dairy	Heart Disease	200	Land (m^2)	1.01	0.28	14.73
Dairy	Mortality	200	Eutrophication (g PO4)	1.01	2.55	33.64
Dairy	Mortality	200	GHGs (g CO2-e)	1.01	218.98	16.1
Dairy	Mortality	200	Irrigation Water (Liters)	1.01	17200	5.32
Dairy	Mortality	200	Land (m^2)	1.01	0.28	14.73
Dairy	Stroke	200	Eutrophication (g PO4)	0.91	2.55	33.64
Dairy	Stroke	200	GHGs (g CO2-e)	0.91	218.98	16.1
Dairy	Stroke	200	Irrigation Water (Liters)	0.91	17200	5.32
Dairy	Stroke	200	Land (m^2)	0.91	0.28	14.73
Eggs	Diabetes	21.4	Eutrophication (g PO4)	1.03	0.62	7.76
Eggs	Diabetes	21.4	GHGs (g CO2-e)	1.03	70.78	4.91
Eggs	Diabetes	21.4	Irrigation Water (Liters)	1.03	5228.57	1.53
Eggs	Diabetes	21.4	Land (m^2)	1.03	0.1	5.13
Eggs	Heart Disease	50	Eutrophication (g PO4)	0.99	1.46	19.18
Eggs	Heart Disease	50	GHGs (g CO2-e)	0.99	165.16	12.14
Eggs	Heart Disease	50	Irrigation Water (Liters)	0.99	12200	3.77
Eggs	Heart Disease	50	Land (m^2)	0.99	0.24	12.69
Eggs	Mortality	47.3	Eutrophication (g PO4)	0.96	1.38	19.18
Eggs	Mortality	47.3	GHGs (g CO2-e)	0.96	156.22	12.14
Eggs	Mortality	47.3	Irrigation Water	0.96	11539.75	3.77
Eggs	Mortality	47.3	Land (m^2)	0.96	0.23	12.69
Eggs	Stroke	50	Eutrophication (g PO4)	0.91	1.46	19.18
Eggs	Stroke	50	GHGs (g CO2-e)	0.91	165.16	12.14
Eggs	Stroke	50	Irrigation Water (Liters)	0.91	12200	3.77
Eggs	Stroke	50	Land (m^2)	0.91	0.24	12.69
Fish	Diabetes	14.3	Eutrophication (g PO4)	1.01	0.11	1.33
Fish	Diabetes	14.3	GHGs (g CO2-e)	1.01	100.81	6.99
Fish	Diabetes	14.3	Irrigation Water (Liters)	1.01	1468.24	0.43
Fish	Diabetes	14.3	Land (m^2)	1.01	0.09	4.65
Fish	Heart Disease	15	Eutrophication (g PO4)	0.94	0.11	1.48
Fish	Heart Disease	15	GHGs (g CO2-e)	0.94	105.85	7.78
Fish	Heart Disease	15	Irrigation Water (Liters)	0.94	1541.65	0.48
Fish	Heart Disease	15	Land (m^2)	0.94	0.1	5.18
Fish	Mortality	20	Eutrophication (g PO4)	0.94	0.15	1.97
Fish	Mortality	20	GHGs (g CO2-e)	0.94	141.13	10.37
Fish	Mortality	20	Irrigation Water (Liters)	0.94	2055.53	0.64
Fish	Mortality	20	Land (m^2)	0.94	0.13	6.9
Fish	Stroke	42.9	Eutrophication (g PO4)	0.94	0.32	4.22
Fish	Stroke	42.9	GHGs (g CO2-e)	0.94	302.43	22.23
Fish	Stroke	42.9	Irrigation Water (Liters)	0.94	4404.71	1.36
Fish	Stroke	42.9	Land (m^2)	0.94	0.28	14.79

Food Group	Disease Endpoint	Serving size (g)	Environmental Indicator	Relative Risk of Disease	Environmental Impact per serving of food	Relative Environmental Impact per serving of food (baseline = vegetables)
Fruits	Diabetes	106	Eutrophication (g PO4)	0.99	0.51	6.3
Fruits	Diabetes	106	GHGs (g CO2-e)	0.99	15.5	1.08
Fruits	Diabetes	106	Irrigation Water (Liters)	0.99	11649.15	3.4
Fruits	Diabetes	106	Land (m^2)	0.99	0.03	1.63
Fruits	Heart Disease	100	Eutrophication (g PO4)	0.86	0.48	6.3
Fruits	Heart Disease	100	GHGs (g CO2-e)	0.86	14.63	1.08
Fruits	Heart Disease	100	Irrigation Water (Liters)	0.86	10989.76	3.4
Fruits	Heart Disease	100	Land (m^2)	0.86	0.03	1.63
Fruits	Mortality	100	Eutrophication (g PO4)	0.89	0.48	6.3
Fruits	Mortality	100	GHGs (g CO2-e)	0.89	14.63	1.08
Fruits	Mortality	100	Irrigation Water (Liters)	0.89	10989.76	3.4
Fruits	Mortality	100	Land (m^2)	0.89	0.03	1.63
Fruits	Stroke	100	Eutrophication (g PO4)	0.86	0.48	6.3
Fruits	Stroke	100	GHGs (g CO2-e)	0.86	14.63	1.08
Fruits	Stroke	100	Irrigation Water (Liters)	0.86	10989.76	3.4
Fruits	Stroke	100	Land (m^2)	0.86	0.03	1.63
Legumes	Diabetes	19	Eutrophication (g PO4)	0.78	0.04	0.5
Legumes	Diabetes	19	GHGs (g CO2-e)	0.78	4.33	0.3
Legumes	Diabetes	19	Irrigation Water (Liters)	0.78	2633.39	0.77
Legumes	Diabetes	19	Land (m^2)	0.78	0.09	4.29
Legumes	Heart Disease	19	Eutrophication (g PO4)	0.86	0.04	0.53
Legumes	Heart Disease	19	GHGs (g CO2-e)	0.86	4.33	0.32
Legumes	Heart Disease	19	Irrigation Water (Liters)	0.86	2633.39	0.81
Legumes	Heart Disease	19	Land (m^2)	0.86	0.09	4.54
Legumes	Mortality	19	Eutrophication (g PO4)	0.9	0.04	0.53
Legumes	Mortality	19	GHGs (g CO2-e)	0.9	4.33	0.32
Legumes	Mortality	19	Irrigation Water	0.9	2633.39	0.81
Legumes	Mortality	19	Land (m^2)	0.9	0.09	4.54
Legumes	Stroke	19	Eutrophication (g PO4)	0.98	0.04	0.53
Legumes	Stroke	19	GHGs (g CO2-e)	0.98	4.33	0.32
Legumes	Stroke	19	Irrigation Water (Liters)	0.98	2633.39	0.81
Legumes	Stroke	19	Land (m^2)	0.98	0.09	4.54
Nuts	Diabetes	16.2	GHGs (g CO2-e)	0.87	18.79	1.3
Nuts	Diabetes	16.2	Irrigation Water (Liters)	0.87	15596.07	4.55
Nuts	Diabetes	16.2	Land (m^2)	0.87	0.1	5.03
Nuts	Heart Disease	16.2	GHGs (g CO2-e)	0.78	18.79	1.38
Nuts	Heart Disease	16.2	Irrigation Water (Liters)	0.78	15596.07	4.82
Nuts	Heart Disease	16.2	Land (m^2)	0.78	0.1	5.34
Nuts	Mortality	28	GHGs (g CO2-e)	0.78	32.42	2.38
Nuts	Mortality	28	Irrigation Water (Liters)	0.78	26908.72	8.32
Nuts	Mortality	28	Land (m^2)	0.78	0.18	9.21
Nuts	Stroke	16.2	GHGs (g CO2-e)	0.89	18.79	1.38
Nuts	Stroke	16.2	Irrigation Water (Liters)	0.89	15596.07	4.82
Nuts	Stroke	16.2	Land (m^2)	0.89	0.1	5.34
Processed red meat	Diabetes	50	Eutrophication (g PO4)	1.32	7.16	88.96
Processed red meat	Diabetes	50	GHGs (g CO2-e)	1.32	1070.97	74.27
Processed red meat	Diabetes	50	Irrigation Water (Liters)	1.32	24531.35	7.16
Processed red meat	Diabetes	50	Land (m^2)	1.32	4.48	220.32
Processed red meat	Heart Disease	50	Eutrophication (g PO4)	1.15	7.16	94.3
Processed red meat	Heart Disease	50	GHGs (g CO2-e)	1.15	1070.97	78.73
Processed red meat	Heart Disease	50	Irrigation Water (Liters)	1.15	24531.35	7.59
Processed red meat	Heart Disease	50	Land (m^2)	1.15	4.48	233.54
Processed red meat	Mortality	50	Eutrophication (g PO4 eq	1.15	7.16	94.3
Processed red meat	Mortality	50	GHGs (g CO2-e)	1.15	1070.97	78.73
Processed red meat	Mortality	50	Irrigation Water (Liters)	1.15	24531.35	7.59
Processed red meat	Mortality	50	Land (m^2)	1.15	4.48	233.54
Processed red meat	Stroke	50	Eutrophication (g PO4)	1.11	7.16	94.3
Processed red meat	Stroke	50	GHGs (g CO2-e)	1.11	1070.97	78.73
Processed red meat	Stroke	50	Irrigation Water (Liters)	1.11	24531.35	7.59
Processed red meat	Stroke	50	Land (m^2)	1.11	4.48	233.54

Food Group	Disease Endpoint	Serving size (g)	Environmental Indicator	Relative Risk of Disease	Environmental Impact per serving of food	Relative Environmental Impact per serving of food (baseline = vegetables)
SSBs	Diabetes	250	Eutrophication (g PO4)	1.27	0.06	0.76
SSBs	Diabetes	250	GHGs (g CO2-e)	1.27	20.44	1.42
SSBs	Diabetes	250	Irrigation Water (Liters)	1.27	1329.54	0.39
SSBs	Diabetes	250	Land (m^2)	1.27	0.03	1.54
SSBs	Heart Disease	335	Eutrophication (g PO4)	1.16	0.08	1.08
SSBs	Heart Disease	335	GHGs (g CO2-e)	1.16	27.39	2.01
SSBs	Heart Disease	335	Irrigation Water (Liters)	1.16	1781.58	0.55
SSBs	Heart Disease	335	Land (m^2)	1.16	0.04	2.18
SSBs	Mortality	308.8	Eutrophication (g PO4)	1.13	0.08	1.08
SSBs	Mortality	308.8	GHGs (g CO2-e)	1.13	25.24	2.01
SSBs	Mortality	308.8	Irrigation Water	1.13	1641.99	0.55
SSBs	Mortality	308.8	Land (m^2)	1.13	0.04	2.18
SSBs	Stroke	292.5	Eutrophication (g PO4)	1.06	0.07	0.94
SSBs	Stroke	292.5	GHGs (g CO2-e)	1.06	23.91	1.76
SSBs	Stroke	292.5	Irrigation Water (Liters)	1.06	1555.56	0.48
SSBs	Stroke	292.5	Land (m^2)	1.06	0.04	1.91
Sugar	Heart Disease	42.9	Eutrophication (g PO4)	1.18	0.11	1.39
Sugar	Heart Disease	42.9	GHGs (g CO2-e)	1.18	35.07	2.58
Sugar	Heart Disease	42.9	Irrigation Water (Liters)	1.18	2281.49	0.71
Sugar	Heart Disease	42.9	Land (m^2)	1.18	0.05	2.8
Sugar	Mortality	42	Eutrophication (g PO4)	1	0.1	1.36
Sugar	Mortality	42	GHGs (g CO2-e)	1	34.33	2.52
Sugar	Mortality	42	Irrigation Water (Liters)	1	2233.63	0.69
Sugar	Mortality	42	Land (m^2)	1	0.05	2.74
Unprocessed red meat	Diabetes	100	Eutrophication (g PO4)	1.13	14.31	177.93
Unprocessed red meat	Diabetes	100	GHGs (g CO2-e)	1.13	2141.93	148.54
Unprocessed red meat	Diabetes	100	Irrigation Water (Liters)	1.13	49062.69	14.32
Unprocessed red meat	Diabetes	100	Land (m^2)	1.13	8.96	440.63
Unprocessed red meat	Heart Disease	100	Eutrophication (g PO4)	1.06	14.31	188.6
Unprocessed red meat	Heart Disease	100	GHGs (g CO2-e)	1.06	2141.93	157.45
Unprocessed red meat	Heart Disease	100	Irrigation Water (Liters)	1.06	49062.69	15.18
Unprocessed red meat	Heart Disease	100	Land (m^2)	1.06	8.96	467.07
Unprocessed red meat	Mortality	100	Eutrophication (g PO4)	1.05	14.31	188.6
Unprocessed red meat	Mortality	100	GHGs (g CO2-e)	1.05	2141.93	157.45
Unprocessed red meat	Mortality	100	Irrigation Water (Liters)	1.05	49062.69	15.18
Unprocessed red meat	Mortality	100	Land (m^2)	1.05	8.96	467.07
Unprocessed red meat	Stroke	100	Eutrophication (g PO4)	1.13	14.31	188.6
Unprocessed red meat	Stroke	100	GHGs (g CO2-e)	1.13	2141.93	157.45
Unprocessed red meat	Stroke	100	Irrigation Water (Liters)	1.13	49062.69	15.18
Unprocessed red meat	Stroke	100	Land (m^2)	1.13	8.96	467.07
Vegetables	Diabetes	106	Eutrophication (g PO4)	0.98	0.08	1
Vegetables	Diabetes	106	GHGs (g CO2-e)	0.98	14.42	1
Vegetables	Diabetes	106	Irrigation Water (Liters)	0.98	3427.11	1
Vegetables	Diabetes	106	Land (m^2)	0.98	0.02	1
Vegetables	Heart Disease	100	Eutrophication (g PO4)	0.91	0.08	1
Vegetables	Heart Disease	100	GHGs (g CO2-e)	0.91	13.6	1
Vegetables	Heart Disease	100	Irrigation Water (Liters)	0.91	3233.12	1
Vegetables	Heart Disease	100	Land (m^2)	0.91	0.02	1
Vegetables	Mortality	100	Eutrophication (g PO4)	0.87	0.08	1
Vegetables	Mortality	100	GHGs (g CO2-e)	0.87	13.6	1
Vegetables	Mortality	100	Irrigation Water (Liters)	0.87	3233.12	1
Vegetables	Mortality	100	Land (m^2)	0.87	0.02	1
Vegetables	Stroke	100	Eutrophication (g PO4)	0.86	0.08	1
Vegetables	Stroke	100	GHGs (g CO2-e)	0.86	13.6	1
Vegetables	Stroke	100	Irrigation Water (Liters)	0.86	3233.12	1
Vegetables	Stroke	100	Land (m^2)	0.86	0.02	1

Food Group	Disease Endpoint	Serving size (g)	Environmental Indicator	Relative Risk of Disease	Environmental Impact per serving of food	Relative Environmental Impact per serving of food (baseline = vegetables)
Whole grains	Diabetes	30	Eutrophication (g PO4)	0.68	0.17	2.06
Whole grains	Diabetes	30	GHGs (g CO2-e)	0.68	30.52	2.12
Whole grains	Diabetes	30	Irrigation Water (Liters)	0.68	8767.11	2.56
Whole grains	Diabetes	30	Land (m^2)	0.68	0.11	5.35
Whole grains	Heart Disease	30	Eutrophication (g PO4)	0.8	0.17	2.18
Whole grains	Heart Disease	30	GHGs (g CO2-e)	0.8	30.52	2.24
Whole grains	Heart Disease	30	Irrigation Water (Liters)	0.8	8767.11	2.71
Whole grains	Heart Disease	30	Land (m^2)	0.8	0.11	5.67
Whole grains	Mortality	30	Eutrophication (g PO4)	0.82	0.17	2.18
Whole grains	Mortality	30	GHGs (g CO2-e)	0.82	30.52	2.24
Whole grains	Mortality	30	Irrigation Water (Liters)	0.82	8767.11	2.71
Whole grains	Mortality	30	Land (m^2)	0.82	0.11	5.67
Whole grains	Stroke	30	Eutrophication (g PO4)	0.88	0.17	2.18
Whole grains	Stroke	30	GHGs (g CO2-e)	0.88	30.52	2.24
Whole grains	Stroke	30	Irrigation Water (Liters)	0.88	8767.11	2.71
Whole grains	Stroke	30	Land (m^2)	0.88	0.11	5.67

Table S2. Underlying health and environmental data used in Chapter 3.

Chapter 4:

Supplementary Methods

Projecting future changes in cropland and pastureland

We forecasted spatially explicit patterns of cropland and pastureland from 2010 to 2060 at 2.25km^2 resolution (1.5 x 1.5km cells). We did so by first developing a two-stage model framework that models past changes in agricultural land for each cell based on that cell's current extent of cropland and pastureland (DAAC, 2017); its historical change in cropland and pastureland (DAAC, 2017); its agricultural suitability (FAO & IIASA, 2017); how far it is from a city (Weiss et al., 2018); and whether it contains a protected area (UNEP & IUCN, 2017). We then linked the two-part model framework to country-level forecasts of cropland demand to forecast the spatial location of cropland and pastureland for every 5 years from 2010 to 2060 for 39 nations.

Modeling past changes in agricultural land

We used a two-stage model framework to understand the historic drivers of cropland change and to forecast the future location of cropland. First, we built a multinomial regression model to estimate the probability that a cell experienced a change in cropland extent. We then built generalized linear models (GLMs) to explain the magnitude of this change.

Cropland tends to expand from currently cultivated areas into areas at the margin of current agricultural land, into areas with high suitability for crop production (Prishchepov et al., 2011), and into areas that have better access to markets and agricultural inputs (e.g. fertilizer, improved seeds, etc; Prishchepov et al., 2011). Conversely, protected areas (PAs) tend to slow agricultural expansion, although do not universally stop it, both through design – for example IUCN Categories V and VI – and imperfect enforcement (e.g. Andam et al., 2008). We therefore included measures of these factors in both the multinomial and GLM models.

We used the same two-stage model framework to understand the drivers of pastureland change.

Data used

Table S1 shows the data source for each variable in our modelling approach, the rationale for including the variable, and additional notes. See below for more detail.

Historical Land Cover

We used MODIS Land Cover Type 1 (MCD12Q1 – henceforth "MODIS") for estimates of historical land cover from 2001 to 2013 (DAAC, 2017). MODIS provides estimates of primary land cover class, percent cover of the primary land cover class, and secondary land cover class. We assumed that percent cover of secondary land cover class is the smaller of either (1 – percent cover of primary land cover class) or the percent cover of the primary land cover class.

We extracted land cover data for cropland, pastureland, urban and built-up areas, and uncultivable lands (e.g. cliffs, deserts, etc), aggregating several land cover classes to obtain historic estimates of the historic extent of cropland, pastureland, and uncultivable lands. Specifically, we aggregated "croplands" (MODIS land cover class 12) and "cropland/natural vegetation mosaic" (MODIS land cover class 14) to obtain our measure

of cropland; “savannas” (MODIS land cover class 9) and “grasslands” (MODIS land cover class 10) for our measure pastureland; and “snow and ice” (MODIS land cover class 15), “barren or sparsely vegetated” (MODIS land cover class 16), “water” (MODIS land cover class 0), and “urban and built-up areas” (MODIS land cover class 13) for our measure of uncultivable land.

We extracted MODIS data from 2001 to 2013 to assess and model historic changes in cell-level agricultural land. To account for natural errors in satellite data we calculated the mean cell value for multiple 3-year time periods: 2001-2003 (hereafter “2002”); 2004-2006 (‘2005”); 2006-2008 (“2007”), 2009-2011 (“2010”), and 2011-2013 (“2012”).

Because agriculture often expands at the margin of current agriculture, we also calculated the proportion of cropland and pastureland in the immediately adjacent cells in each time period.

Protected Areas

We obtained data on protected areas (PAs) from the World Database of Protected Areas (WDPA) which includes >200,000 PAs in 245 countries and territories (UNEP & IUCN, 2017). We classified cells as containing a PA or not – rather than using the proportion of the cell that is protected – to account for possible inaccuracies in the data and uncertainty over which land cover classes are within the PA.

Travel Time to Urban Areas

We extracted shortest estimated travel time to urban areas of at least 50,000 people from a recent dataset that incorporated roads, railways, and waterways while also adjusting for topography, land cover, and national borders (Weiss et al., 2018).

Agroecological Soil Suitability

Agroecological soil suitability (AESS) is a measure of how suitable land is for crop production (FAO & IIASA, 2017). We used FAO estimates of AESS under high input

and rain-fed agricultural conditions. These are the most "optimistic" estimates provided by the FAO, but are likely lower than estimates of AESS under irrigated conditions.

Because AESS differs between crops, we estimated average AESS for each cell. To do so, we first obtained cell-specific estimates of AESS for 36 crops. We then calculated the proportion of cropland devoted to each of these 36 crops for each nation. We then calculated a weighted mean AESS by weighting each cell's crop-specific estimates of AESS by the national area harvested of that crop (FAO, 2017). We used the weighted mean AESS as an estimate of the cell's average AESS.

Growing Degree Days

Growing degree days (GDD) are an approximation of growing season length. We did not include GDD in our models as a predictor because the underlying AESS incorporates climate variables. However, we limited agricultural expansion in areas with very low GDDs because crop production is unlikely to occur in these areas. Specifically, we prevented agricultural expansion in cells where GDD is less than the 2.5th percentile of GDD weighted by cropland area in 2010 – see "Forecasting the location of future agricultural expansion" unless cropland extent in 2010 was greater than 2.5% of the cell. We estimated GDD by cell using the R package 'gdd'.

Model fitting

We fitted a multinomial regression to estimate the probability of a cell experiencing a change in cropland extent. We then used generalized linear models (GLMs) to explain the magnitude of this change, building separate models for cells that experienced increases and cells that experienced decreases in cropland extent. When developing the model, we used land-cover data from three time periods: 2002 (the first available year – see "Data used"), 2007, and 2012. This enabled us to use changes in cropland extent from 2002 to 2007 to predict how cropland extent changed from 2007 to 2012 (see "Data used").

We used the same explanatory variables for the multinomial and GLM models. Specifically, we included: cropland extent in the cell at the start of the time period (i.e. in 2007); change in cropland in extent over the preceding time period (2002-2007); extent of cropland in the immediately adjacent cells (in 2007); pastureland extent in the cell at the start of the time period (i.e. in 2007); agroecological soil suitability; travel time to nearest city (log transformed); and PA presence (binary value). We included quadratic effects for the current amount of cropland and pastureland in the cell (2007), previous change in the amount of cropland in the cell (2002 – 2007), the extent of cropland in surrounding cells (in 2007), and travel time to the nearest city. In addition, we included country as a fixed effect to account for potential differences in how laws, policies, and overall demand for agricultural land affect the spatial pattern of cropland expansion. See "Data used" and **Table S1** for details on explanatory variables.

Probability of Changes in Cropland Extent

We used a multinomial regression model from the R package "nnet" to estimate the probability that a cell increased, decreased, or did not change in cropland extent from 2007 to 2012. To do so, we first classified each cell as having increased, decreased, or not changed in cropland extent from 2007 to 2012. To account for small errors and uncertainty in MODIS data (Verburg et al., 2011), we classified cells as having changed in cropland extent if cropland extent in a cell changed by more than 2.5% of the cell from 2007 to 2012 (e.g. a cell "increased" in cropland extent if cropland occupied 50% of a cell in 2007 and 55% in 2012; "decreased" in cropland extent if cropland occupied 55% of a cell in 2007 and 50% in 2012; and "did not change" in cropland extent if cropland occupied 50% of a cell in 2007 and 51% in 2012).

We then estimated the probability that a cell "increased", "decreased", or "did not change" in cropland extent from 2007 to 2012 using a multinomial model. The predictor variables used were the proportion of a cell in cropland in 2007, proportion of a cell in pastureland in 2007, change in the proportion of a cell in cropland from 2002 to 2007, travel time to urban areas, AESS, and whether the cell contain any amount of a PA (see

"Data used"). The multinomial model was ~76% accurate at identifying the direction (increase, decrease, or no change) in historic cropland extent.

Cells that contained any amount of a PA, that had lower AESS, and were farther away from cities (by time) were less likely to experience a future increase in cropland extent. Our model estimates are similar to what has been observed before using empirical data (e.g. PAs decrease agricultural expansion (Andam et al., 2008); more cropland in areas with higher soil fertility (Prishchepov et al., 2011) or to what has been predicted in theory (e.g. less expansion further away from cities because of increased cost of transportation (Prishchepov et al., 2011).

Cells that had cropland expansion between 2002 and 2007 were more likely to experience a future increase in cropland extent, while cells with more cropland or pastureland were also more likely to experience a future increase in cropland extent. See **Table S2** for the multinomial model coefficients.

Magnitude of Cropland Extent Change

We then used a generalized linear model (GLM) with gamma distributed errors and a log link to estimate the magnitude of change in cropland extent (how much the amount of cropland in a cell is predicted to change) for each cell based on the same predictor variables (see **Model Validation** for more details). The outcome variable used was the change in amount of cropland in the cell from 2007 to 2012. We fitted separate models to cells that increased or decreased in cropland extent (termed "expansion GLMs" and "contraction GLMs" respectively) because the drivers of cropland contraction and expansion differ (**Table S1**). See **Table S3** for model coefficients.

The predictor variables most strongly associated with the expected future change in cropland extent were the current extent of agricultural land and the change in extent of cropland in the 5-year time interval. There is an inverse quadratic relationship between current extent of cropland and the expected future magnitude of cropland change – that is

cells with intermediate amounts of cropland are projected to have the largest increase in future cropland extent. A similar association was observed between current cropland extent and the projected decrease in future cropland extent.

The existence of a PA, travel time to cities, and agroecological soil suitability all have a comparatively small effect on the modeled change in the amount of cropland in a cell. The existence of a PA in a cell and travel time to cities decreases the predicted increase and increases the predicted decrease in the amount of cropland in a cell. In contrast, cells with higher agroecological soil suitability are predicted to have larger increases and smaller decreases in the amount of cropland in a cell.

Pastureland

We used the same two-stage modelling approach to estimate the probability each cell will experience pastureland expansion and the expected magnitude of pastureland expansion. We used the same explanatory variables as for cropland, but used change in pastureland extent from 2002 to 2007 (and its quadratic) and the extent of pastureland in neighboring cells (and its quadratic), instead of the change in cropland extent from 2002 to 2007 (and its quadratic) and the extent of cropland in neighbouring cells (and its quadratic), respectively. See **Table S2** for model coefficients for the multinomial model and **Table S4** for model coefficients for the GLM model.

The results from the pastureland model are similar to the results from the cropland model. That is, cells that contained a PA, that had lower agroecological soil suitability, and that contained more pastureland were more likely to experience a future decrease in pasture extent. There is an inverse quadratic relationship between current extent of pastureland and the projected future increase in pastureland extent, and a quadratic relationship between the extent change in pastureland in the previous time interval and the projected future change in pastureland extent.

Model Testing and Validation

Model Testing

We also tested other model forms for both model stages (probability of change and magnitude of change). For the probability of change, we also examined how a model fit using a Gradient Boosting Machine (GBM; a form of machine learning). Model accuracy when identifying the historic direction of change (e.g. increase, decrease, or no change in extent) in cropland or pastureland was often slightly higher (normally 2-5% across geographic regions). However, the GBM model does not provide coefficient estimates for the model predictors and therefore does not allow us to examine whether estimates for individual predictors are similar to what has been proposed in theory or been found in other empirical analyses. For this reason, we decided to use a multinomial model when predicting the expected probability that a cell will experience a future change in agricultural extent.

When estimating how much the amount of cropland and pastureland is predicted to change in a cell, we also examined a multiple linear regression model with normally distributed errors, a GLM model with inverse Gaussian distributed errors and a log link, and a GBM model. Model fits using these model types were either less accurate or had inconsistent residual structures. Specifically, the multiple linear regression model had residuals that increased with prediction size; the GLM model with an inverse Gaussian error structure and a log link consistently over-predicted at low values under-predicted at high values across all regions and predicted that agricultural extent could change more than the entire cell area (e.g. predicted proportion of change in cropland or pastureland extent > 1); and the GBM model had an inconsistent residual structure (Figure S1).

Model Validation on Historical Data

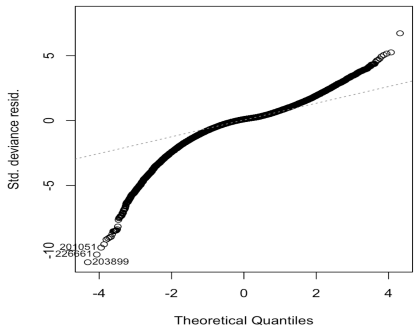
We tested the accuracy of our model by predicting agricultural land cover change from 2007 to 2012 using our two step process. To do this, we first projected the 2012 location of agricultural land using our two-step model process as described above, using the location of agricultural land in 2007 as the baseline. We repeated this process 25 times to get an expected mean value of the proportion of a cell occupied by cropland or

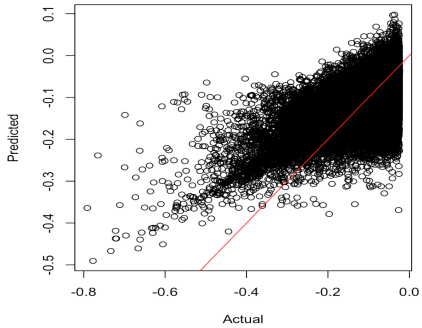
pastureland, as well as the expected variation around the mean value. We then compared our predictions for the location of cropland and pastureland in 2012 with historic 2012 data.

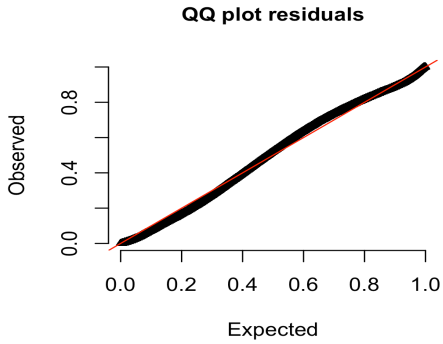
Our model provides predictions of the location in agricultural land that are similar to the historic location of land in 2012 (**Figure S2**). Across all cells in Sub-Saharan Africa, the median difference between our predictions of 2012 cropland extent and historic cropland extent is 0 while the mean difference is -0.003 proportions of a cell. Across cells predicted to experience a change in cropland extent from 2007 to 2012, the median difference between our predictions and historic cropland extent is 6e-5 proportions of a cell while the mean difference is ~0.0038 proportions of a cell. For pasture, the median and mean difference between our predictions of 2012 pastureland extent and historic pastureland extent are 0.004 and 0.0139 proportions of a cell, respectively, when examining all cells in Sub-Saharan Africa. When looks across only cells that we projected to experience a change in pastureland extent, the median and mean difference between our predictions of 2012 pastureland extent and historic pastureland extent are 0.007 and 0.014 proportions of a cell, respectively.

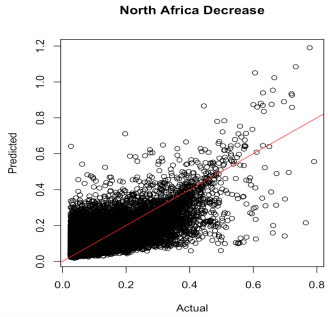
Because we repeated our forecast of the predicted amount of agricultural land in each cell 25 times, we were also able to look at the cells where the historic amount of agricultural land in a cell was not within the mean +- one standard deviation of the predicted amount of agricultural land in the cell (**Figure S2**). In doing so, this shows that the predicted amount of a cell in cropland is within one standard deviation of the historic amount of cropland in the cell ~86.5% of the time. When looking at the predicted amount of pastureland in a cell, this shows that the predicted amount of a cell in pastureland is within one standard deviation of the historic amount of pastureland in the cell ~97.9% of the time.

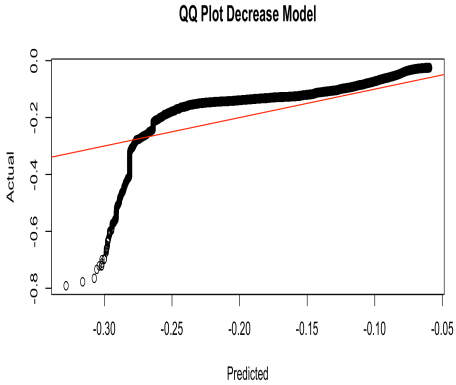
QQ Plot Actual vs Predicted

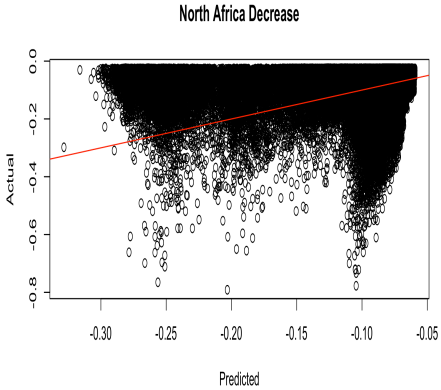


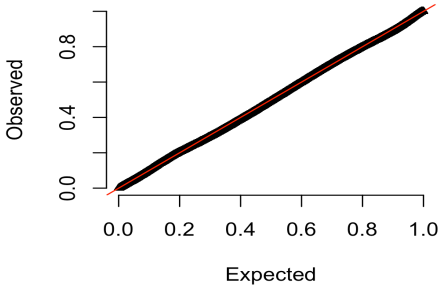












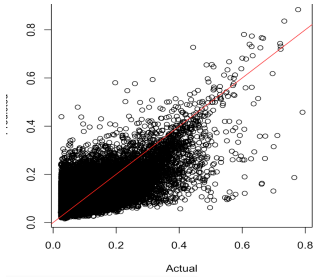


Figure S1. QQ plots and plots of actual vs predicted for values for, from top to bottom, a linear multiple regression model with normally distributed errors, and generalized linear model (GLM) with an inverse Gaussian error structure and log link, a Gradient Boosting Machine model, and a GLM with a gamma error structure and a log link.

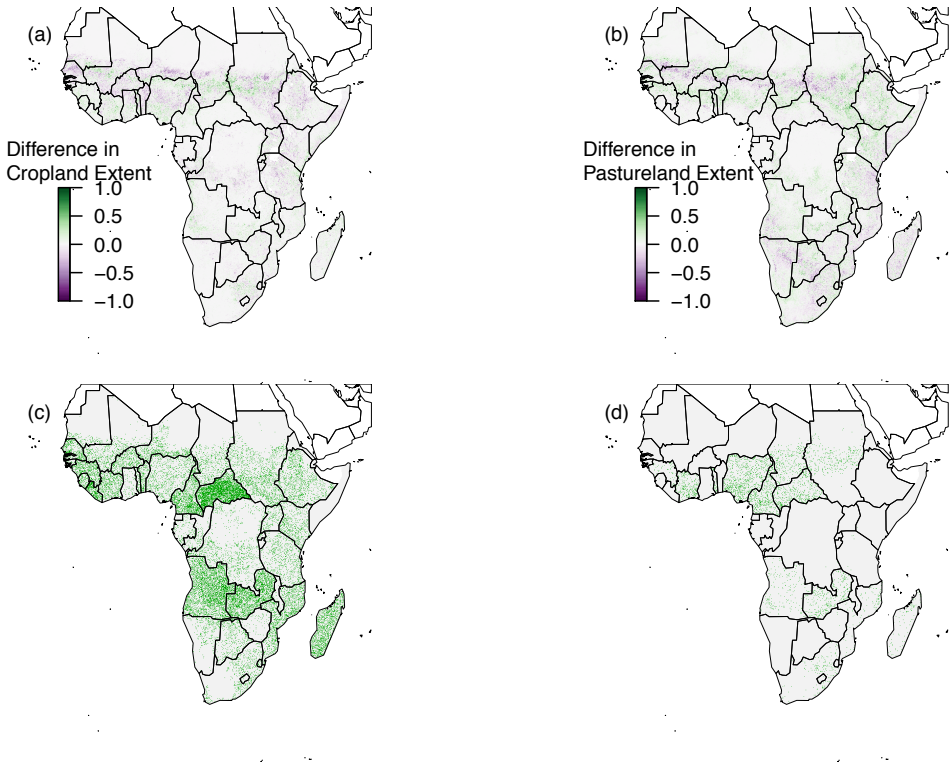


Figure S2. Differences between our predictions of 2012 agricultural extent and reported 2012 agricultural extent. **(a,b)** Difference in the proportion of a cell occupied by **(a)** cropland or **(b)** pastureland between our predictions of 2012 agricultural extent and reported MODIS agricultural extent in 2012. Positive values indicate that we overpredicted the amount of agriculture in a cell, whereas negative values indicate that we underpredicted the amount of agriculture in a cell. **(c,d)** Green indicates cells where historic values of the amount of a cell in **(c)** cropland or **(d)** pastureland were not within one standard deviation of our predicted amount of cropland or pastureland.

Forecasting the extent of agricultural expansion under Business-As-Usual

We forecasted increases in cropland demand for Sub-Saharan African nations at 5-year intervals from 2010-2060 using methods from Tilman et al (2017), based on historical dietary, crop yield, and per capita GDP trends, as well as forecasts of diets, crop yields, per capita GDP, and population trends. Further, our forecasts of cropland demand were not allowed to exceed the FAO's estimates of potentially arable land (e.g. the amount of land suitable for crop production). Because MODIS and FAO estimates of cropland differ due to differences in how they are estimated, we harmonized these datasets before forecasting cropland demand such that the forecasted increase in cropland demand, when applied to MODIS cropland extent in 2010, could not exceed the FAO's estimates of potentially arable land. We term the change in demand in each country in each time period as the "5-year target". We assumed the area of pastureland remained constant for each country, following recent patterns (FAO, 2017).

Forecasting the location of agricultural expansion

To forecast the location of future agricultural land within each nation, we linked our country-level forecasts of cropland demand to our two-stage model framework, assigning cropland to cells based on their probability of change and the predicted magnitude of this change.

To do this, we selected cells at random within each nation based on their relative probabilities that they would see a change in cropland extent. We then estimated the magnitude of this change based on the GLM model. We repeated this random selection until the country's forecasted 5-year target for change in cropland demand was met. For countries projected to see an expansion in cropland, we selected from all cells based on their probability of expansion (i.e. cells could be selected even if they were most likely to show contraction, or no change) and we predicted the magnitude of change using the expansion GLMs. Similarly, for countries projected to see cropland contraction, we selected from all cells based on their probability of contraction and we predicted the magnitude of change using the contraction GLMs.

For each cell selected, we ensured that the proportion of cropland in a cell could not exceed the space available once accounting for uncultivable lands, nor fall below 0%. We further assumed that cropland could not expand into cells where a) agroecological soil suitability equaled 0 (corresponding to cells that are "not suitable for agriculture"; GAEZ 2017) or b) into areas where growing degree days (GDD; a measure of the length of a growing season) are below the weighted 2.5th percentile of GDD (weighted by cropland extent by cell in 2010 – see "Data used"), unless cropland extent in 2010 was at least 2.5% of the cell. Note that cropland extent could decrease in these cells.

While we did not project future changes in countries' areas of pastureland, we did allow cropland to expand into pasture – potentially reducing the area of pasture in a country. We therefore calculated the area of pasture lost to cropland and used this as a 5-year target for pasture, repeating the process above but using the region-specific pastureland multinomial models and GLMs with the added condition that pasture cannot expand into existing cropland. If pastureland extent could not expand adequately to meet the 5-year target, we assumed shortfalls would be made up through livestock intensification.

To account for the probabilistic nature of our forecasts, we repeated this process 10 times, and calculated the mean and standard deviation of the extent of cropland and pasture in each cell for each 5-year time period (see **Figure S2** for projected standard deviation in projected cropland extent in the BAU scenario in 2060). To test whether we had done enough model iterations, we examined how the standard deviation of projected cell extent varied by the number of forecast iterations. We did so by randomly selecting a subset of cells that experience a change in agricultural extent, examining how the standard deviation of projected cropland and pastureland extent varied by number of model runs, and then repeating this process 100 times. Doing so reveals that the standard deviation of projected agricultural extent in a cell remains constant after ~15 iterations, thereby indicating that ~15 iterations of the land expansion forecasts should ultimately be conducted (**Figure S4**).

Future land use under alternative scenarios

To investigate the impact of proactive policies to reduce future cropland demand, we also forecasted the location of agricultural land under four alternative scenarios. By 2060, each scenario would individually reduce cropland demand by at least 65 million hectares, while simultaneous adoption of all three scenarios would reduce cropland demand by ~290 million hectares. The scenarios examined here are (1) crop yields, or where yield gaps are closed by 80%, (2) dietary change, or where half of the meat in a diet is instead consumed as dairy and eggs, (3) a trade for land sparing scenario, or where agricultural production is shifted from regions with low yields to regions with high, and (4) combined adoption of the above three scenarios. Adoption of each of these scenarios is gradual, and complete adoption only occurs in 2060. See Tilman et al 2017 for a detailed description of these scenarios.

These alternative scenarios provided alternative 5-year targets of cropland demand for each country. We then projected the spatial location of future agricultural land using the same process as for the Business-As-Usual scenario (**Figure S5**). Deviation around the expected mean value of agricultural land in the alternative scenarios was similar to the deviation in the BAU scenario (**Figures S6-S9**).

Projecting changes in remaining Area of Habitat

We linked our forecasts of agricultural land expansion to existing habitat suitability models (e.g. ref (Rondinini et al., 2011)) for 2072 species of birds that had habitat ranges >= 95% within Sub-Saharan Africa. Habitat suitability models first estimate the extent of suitable habitat (ESH), or an estimate of the maximum historic extent of a species' habitat range, by adjusting IUCN estimates of a species' habitat range with species characteristics (e.g. elevation range, habitat preferences, etc) assuming complete absence of human activity. Habitat suitability models then estimate the remaining area of habitat (AOH) by adjusting estimates of ESH based on each species' tolerance to human altered habitats (e.g. urban areas, cropland, pastureland, etc).

To calculate changes in AOH, we first calculated the total area of ESH for each species as described above. We then calculated the total area of cropland and pastureland within each species' ESH in 2010 and at the end of each 5-year time interval from 2010 to 2060. We then obtained IUCN Level 2 Habitat Classifications, which indicate how suitable different types of habitat are for each species. We then classified each species as being "tolerant" of cropland if cropland was "suitable" habitat, as being "semi-tolerant" of cropland if cropland was "marginal" habitat, or as being "not-tolerant" of cropland if cropland was neither "suitable" or "marginal" habitat for that species. We repeated this process for pastureland, but also assumed that a species was "tolerant" of pastureland if either pastureland or grassland was "suitable" for that species, was "semi tolerant" of pastureland if either pastureland or grassland was "marginal" but neither was "suitable" for that species, and as "not-tolerant" if neither pastureland or grassland was "suitable" or "marginal" habitat for that species. We included grassland in our estimate of tolerance for pastureland because MODIS satellite data does not differentiate between pastureland and grassland and because many pasturelands in Sub-Saharan Africa are not heavily managed. Changing this assumption such that a species is "tolerant" of pastureland if only pastureland is "suitable" habitat, etc, resulted in a projected mean loss in remaining AOH across all species of ~30.0% (compared to ~28.9% when including habitat suitability of both pastureland and grassland).

We then calculated loss in AOH by assuming that a species "tolerant" (e.g. corresponding with "suitable" habitat) could survive equally well in cropland and primary habitat (e.g. a 2 unit expansion in cropland in a species' ESH resulted in no reduction in that species' AOH), that a species "semi tolerant" (corresponding with "marginal" habitat) of cropland could survive in 50% of cropland (e.g. a 2 unit expansion in cropland in a species' ESH resulted in a 1 unit reduction in that species' AOH), and that a species that is "not tolerant" of cropland could not survive in cropland (e.g. a 2 unit expansion in cropland in a species' ESH resulted in a 2 unit reduction in that species' AOH).

Classifying Species for analyses

Tolerance to Agriculture

We classified as being "Tolerant" to agriculture if both cropland and pastureland/grassland were classified as "suitable" habitat for the species; as "Semi-Tolerant" of agriculture if either cropland or pastureland/grassland was at least "marginal" habitat for that species; and as "Not Tolerant" of agriculture if neither cropland or pastureland/grass was "marginal" or "suitable" habitat for that species.

Specialist vs Generalist

We classified species as "Specialist" or "Generalist" species based on the number of habitats that are "suitable" for that species. "Specialist" species are those that have a single "suitable" habitat; "generalist" species are those that have more than one "suitable" habitat (note that all species have at least one "suitable" habitat).

Habitat Preferences

We classified species as having different habitat preferences based on IUCN Level 1 Habitat Classification Scheme. Species were classified as having a preference for a habitat if that habitat is classified as being "suitable" for that species.

Mass Class

We classified species as being "large" if their average body mass is > 2kg; as being "medium" if their average body mass is <2kg and >= 0.5kg; and as being "small" if their body mass is <0.5kg. Body masses were obtained from the IUCN; species that did not have reported body mass were assumed to have the average body mass of all other species in the same genus.

Supplemental Tables.

Table S1. Explanatory variables, underlying data, and rationale for their inclusion in our analyses.

Variable	Rationale for inclusion	Data used	Notes
Proportion of cell in cropland	Cropland is more likely to expand in areas that already have cropland	MODIS Land Cover Type 1 (MCD12Q1); sum of MODIS Land Cover Classes 12 and 14	
Proportion of surrounding cells in cropland	Cropland is more likely to expand at the margin of existing cropland	MODIS Land Cover Type 1 (MCD12Q1); sum of MODIS Land Cover Classes 12 and 14	Used as explanatory variable for cropland expansion only (not pastureland)
Proportion of cell in pasture	Pasture is more likely to expand in areas that already have pastureland; cropland is more likely to expand into pasture than natural habitats	MODIS Land Cover Type 1 (MCD12Q1); sum of MODIS Land Cover Classes 9 and 10	
Proportion of surrounding cells in pasture	Pasture is more likely to expand in areas that already	MODIS Land Cover Type 1 (MCD12Q1); sum	Used as explanatory variable for pastureland

	have pastureland; cropland is more likely to expand into pasture than natural habitats	of MODIS Land Cover Classes 9 and 10	expansion only (not cropland)
Agroecological soil suitability	Agriculture is more likely to expand where soils, climate, and topography are favourable for crop production. While the underlying data is specific to cropland extent, we also included this variable in the model for pastureland because it is also a proxy for the productivity of pastures	FAO Global Agro-Ecological Zones (GAEZ)	
Travel time to nearest city	Agricultural expansion is more likely in areas with better access to cities, to provide access to inputs, markets, investment, and labour.	Weiss et al (2018)	Underlying data estimates minimum travel time to cities based on extent of roads, waterways, and railways.
Protected area	Agricultural	World Database on	Used as an

presence	expansion is less likely to occur (although is not impossible) in protected areas	Protected Areas (2017)	explanatory variable – agricultural expansion was still possible in protected areas, reflecting both the multiple uses of many protected areas [REF] and the imperfect protection of others [REF]
Proportion of uncultivable land in cell	Neither cropland nor pasture will expand into uncultivable lands	MODIS Land Cover Type 1 (MCD12Q1); sum of MODIS Land Cover Classes 0, 15, 16, and 13	Not used as an explanatory variable, but as a mask – preventing agricultural expansion into uncultivable lands

Table S2. Model coefficients for the multinomial models predicting the probability of a cell to experience a change in agricultural extent. Models were fit using R package "nnet". Coefficients for probability that a cell "Has not changed" in agricultural extent in the previous time period are 1. The contribution of individual variables to the probability of a cell to experience an increase in cropland extent can be calculated as coefficient increase / (coefficient increase + coefficient decrease + 1). NAs indicate variables that were not included in the model.

	Cropland Model		Pastureland Model	
Predictor Variable	Relative Probability to Decrease	Relative Probability to Increase	Relative Probability to Decrease	Relative Probability to Increase
Intercept	0.09	0.08	0.35	0.26
log(travel time to cities)	1.11	1.1	1.08	1.1
log(travel time to cities) squared	0.97	0.97	0.97	0.96
agroecological soil suitability	1.04	1.02	0.98	1
PA Binary	1.09	1.06	1.11	1.01
amount of cropland in neighboring cells	0.12	12.82	NA	NA
amount of cropland in neighboring cells squared	1.09	0.82	NA	NA
amount of cropland in cell	1.15E+13	0	0.44	2.6
amount of cropland in cell squared	0	1.44	5.15	1.37
amount of pastureland in cell	26.32	110.21	1.75E+07	39.86
amount of pastureland in cell squared	0.14	0.02	0	0
previous change in amount of cropland in cell	1.71	0.17	NA	NA
previous change in amount of cropland in cell squared	0.94	10.05	NA	NA
previous change in amount of pastureland in cell	NA	NA	4.15	0.1
previous change in amount of pastureland in cell squared	NA	NA	1.94	10.55
amount of pastureland in neighboring cells	NA	NA	0.92	3.98
amount of pastureland in neighboring cells squared	NA	NA	0.94	0.86

	Cropland Model		Pastureland Model	
Predictor Variable	Relative Probability to Decrease	Relative Probability to Increase	Relative Probability to Decrease	Relative Probability to Increase
Country: BDI	0.35	0.34	0.9	0.17
Country: BEN	0.6	0.58	1.16	0.4
Country: BFA	0.67	0.59	0.85	0.73
Country: BWA	0.94	0.99	0.58	1.4
Country: CAF	0.95	0.39	0.99	1.6
Country: CIV	1.09	0.73	0.71	0.5
Country: CMR	1.47	0.84	0.46	0.56
Country: COD	0.77	0.9	0.69	0.45
Country: COG	0.71	0.83	0.51	0.45
Country: COM	1.28	0.89	0.72	0.32
Country: CPV	1.06	1.56	3.25	0.67
Country: DJI	1.03	0.25	1.23	1.4
Country: ERI	0.93	0.61	1.4	1.05
Country: ETH	1.45	1.12	1.34	0.97
Country: GAB	0.63	1.2	0.19	0.32
Country: GHA	1.06	0.68	0.88	0.48
Country: GIN	1.42	0.84	0.92	0.58
Country: GMB	0.5	0.7	0.97	0.16
Country: GNB	1.1	0.99	1.23	0.4
Country: GNQ	1.11	1.74	0.1	0.29
Country: KEN	1.23	1.12	0.79	0.87
Country: LBR	2.18	1.1	0.11	0.14
Country: MDG	1.24	0.85	0.32	1.93
Country: MLI	0.72	0.71	0.74	0.96
Country: MOZ	0.95	0.82	0.36	1.33
Country: MRT	0.51	0.62	0.68	1.03
Country: MUS	1.24	0.38	0.33	1.27
Country: MWI	0.59	0.5	0.26	0.7
Country: NAM	0.62	0.67	0.82	1.84
Country: NER	0.63	0.59	0.55	0.55
Country: NGA	1.23	0.7	0.69	0.6
Country: RWA	0.58	0.47	0.9	0.28
Country: SDN	0.74	0.54	0.8	0.95
Country: SEN	0.68	0.74	0.8	0.55
Country: SHN	NA	NA	2.3	17.14
Country: SLE	2.77	1.45	0.6	0.68
Country: SOM	2.09	2.23	1.59	1.68
Country: SSD	0.9	0.76	1.37	1.34
Country: STP	1.95	3.48	0.39	1.06
Country: SWZ	0.73	0.63	0.57	0.32
Country: SYC	109.35	0.05	1.81	1.6
Country: TCD	0.74	0.66	0.8	0.99
Country: TGO	0.78	0.47	0.66	0.62
Country: TZA	0.92	0.74	0.48	1.03
Country: UGA	0.73	0.5	0.93	0.41
Country: ZAF	0.65	0.46	0.55	1.17
Country: ZMB	0.74	0.59	0.69	0.66
Country: ZWE	0.93	0.84	0.34	1.08

Table S3. Model coefficients for the generalized linear models models predicting how much the amount of cropland in a cell is projected to change. Models were fit using R package "stats" and assume a gamma distributed errors with a log link. NAs indicate variables that were not included in the model. The "Increase Model" was fit to cells that increased in cropland extent > 0.025 proportions of a cell from 2002 to 2007; the "Decrease Model" was fit to cells that increased in cropland extent < 0.025 proportions of a cell from 2002 to 2007.

	Increase Model				Decrease Model			
Predictor Variable	Estimate	Std. Error	t value	P value	Estimate	Std. Error	t value	P value
Intercept	-3.128	0.003	-1014.545	<0.0001	-3.287	0.002	-1368.485	<0.0001
log(travel time to cities)	0.007	0.001	12.428	<0.0001	0.002	0.0005	3.806	0.0001
log(travel time to cities) squared	-0.0001	1.00E-04	-1.46	0.144	-0.0007	1.00E-04	-11.537	<0.0001
agroecological soil suitability	-0.005	0.0002	-23.988	<0.0001	0.003	0.0002	16.677	<0.0001
PA Binary	0.004	0.001	4.064	<0.0001	0.018	0.001	21.707	<0.0001
amount of cropland in neighboring cells	0.64	0.001	601.207	<0.0001	-0.331	0.001	-371.507	<0.0001
amount of cropland in neighboring cells squared	-0.037	0.0001	-255.553	<0.0001	-0.004	0.0001	-31.261	<0.0001
amount of cropland in cell	-1.013	0.008	-120.445	<0.0001	6.702	0.007	967.715	<0.0001
amount of cropland in cell squared	-1.763	0.01	-176.66	<0.0001	-3.404	0.007	-479.989	<0.0001
amount of pastureland in cell	0.405	0.006	62.696	<0.0001	0.074	0.005	14.005	<0.0001
amount of pastureland in cell squared	-0.408	0.007	-58.377	<0.0001	-0.07	0.006	-11.277	<0.0001
previous change in amount of cropland in cell	-0.249	0.003	-79.592	<0.0001	0.218	0.003	80.167	<0.0001
previous change in amount of cropland in cell squared	0.611	0.01	61.82	<0.0001	0.199	0.007	27.4	<0.0001
Country: BDI	-0.147	0.008	-18.429	<0.0001	-0.18	0.008	-22.74	<0.0001
Country: BEN	0.005	0.004	1.138	0.255	-0.083	0.004	-20.896	<0.0001
Country: BFA	-0.033	0.003	-10.811	<0.0001	-0.028	0.003	-10.467	<0.0001
Country: BWA	0.024	0.003	7.96	<0.0001	-0.032	0.003	-12.965	<0.0001
Country: CAF	-0.08	0.005	-14.81	<0.0001	-0.063	0.003	-25.304	<0.0001
Country: CIV	-0.054	0.003	-15.87	<0.0001	-0.069	0.002	-30.246	<0.0001
Country: CMR	-0.008	0.004	-2.278	0.023	0.004	0.002	1.832	0.067
Country: COD	0.011	0.002	4.598	<0.0001	-0.073	0.002	-39.383	<0.0001
Country: COG	-0.025	0.004	-6.397	<0.0001	-0.088	0.003	-27.459	<0.0001
Country: COM	0.038	0.071	0.531	0.595	-0.018	0.042	-0.425	0.671
Country: CPV	0.213	0.024	8.943	<0.0001	0.054	0.049	1.104	0.269
Country: DJI	-0.033	0.037	-0.892	0.372	0.004	0.012	0.354	0.723
Country: ERI	-0.002	0.007	-0.231	0.817	0.045	0.004	10.407	<0.0001
Country: ETH	-0.034	0.002	-14.963	<0.0001	-0.031	0.002	-17.255	<0.0001
Country: GAB	-0.076	0.005	-14.471	<0.0001	-0.144	0.005	-27.255	<0.0001
Country: GHA	-0.03	0.003	-8.664	<0.0001	-0.028	0.003	-10.496	<0.0001
Country: GIN	0.019	0.004	4.703	<0.0001	-0.017	0.003	-6.805	<0.0001
Country: GMB	0.026	0.012	2.18	0.029	0.072	0.014	5.135	<0.0001
Country: GNB	0.033	0.008	3.942	<0.0001	-0.046	0.007	-6.37	<0.0001
Country: GNQ	0.058	0.014	4.11	<0.0001	-0.179	0.013	-13.485	<0.0001
Country: KEN	-0.004	0.003	-1.391	0.164	-0.025	0.002	-11.961	<0.0001
Country: LBR	0.022	0.009	2.495	0.013	-0.063	0.004	-14.919	<0.0001
Country: MDG	-0.027	0.003	-9.1	<0.0001	-0.011	0.002	-5.132	<0.0001
Country: MLI	0.008	0.002	3.367	0.001	-0.013	0.002	-6.473	<0.0001
Country: MOZ	-0.036	0.003	-13.728	<0.0001	-0.037	0.002	-19.496	<0.0001
Country: MRT	0.056	0.003	16.744	<0.0001	-0.028	0.003	-9.725	<0.0001
Country: MUS	-0.159	0.057	-2.765	0.006	-0.03	0.03	-1.013	0.311
Country: MWI	-0.077	0.005	-15.604	<0.0001	-0.107	0.004	-28.173	<0.0001
Country: NAM	0.064	0.003	19.205	<0.0001	-0.074	0.003	-25.965	<0.0001
Country: NER	0.031	0.003	11.67	<0.0001	0.068	0.002	28.441	<0.0001
Country: NGA	0.013	0.003	5.253	<0.0001	0.072	0.002	38.248	<0.0001
Country: RWA	-0.158	0.009	-17.242	<0.0001	-0.103	0.007	-13.986	<0.0001
Country: SDN	0.027	0.002	11.404	<0.0001	0.044	0.002	24.429	<0.0001
Country: SEN	0.065	0.003	19.334	<0.0001	-0.019	0.003	-5.905	<0.0001
Country: SLE	0.013	0.008	1.78	0.075	0.007	0.004	1.847	0.065
Country: SOM	-0.008	0.003	-2.971	0.003	0.02	0.002	8.598	<0.0001
Country: SSD	0.098	0.003	37.536	<0.0001	-0.025	0.002	-11.888	<0.0001
Country: STP	0.372	0.061	6.053	<0.0001	0.067	0.08	0.838	0.402
Country: SWZ	0.104	0.011	9.549	<0.0001	-0.033	0.01	-3.382	0.001
Country: SYC	NA	NA	NA	NA	0.15	0.151	0.996	0.319
Country: TCD	0.02	0.002	8.077	<0.0001	0.021	0.002	11.297	<0.0001
Country: TGO	-0.06	0.006	-9.504	<0.0001	-0.015	0.004	-3.563	0.0004
Country: TZA	-0.033	0.002	-13.909	<0.0001	-0.034	0.002	-18.473	<0.0001
Country: UGA	-0.034	0.004	-9.493	<0.0001	-0.062	0.003	-22.401	<0.0001
Country: ZAF	0.002	0.003	0.658	0.511	-0.012	0.002	-6.222	<0.0001
Country: ZMB	-0.04	0.003	-13.317	<0.0001	-0.043	0.002	-21.291	<0.0001
Country: ZWE	0.014	0.003	4.568	<0.0001	-0.021	0.002	-9.384	<0.0001

Table S4. Model coefficients for the generalized linear models models predicting how much the amount of pastureland in a cell is projected to change. Models were fit using R package "stats" and assume a gamma distributed errors with a log link. NAs indicate variables that were not included in the model. The "Increase Model" was fit to cells that increased in pastureland extent > 0.025 proportions of a cell from 2002 to 2007.

	Increase Model			
Predictor Variable	Estimate	Std. Error	t value	P value
Intercept	-2.974	0.003	-917.2	<0.0001
log(travel time to cities)	0.011	0.001	16.94	<0.0001
log(travel time to cities) squared	-0.003	1.00E-04	-36.16	<0.0001
agroecological soil suitability	0.008	0.0002	41.99	<0.0001
PA Binary	-0.005	0.001	-4.82	<0.0001
amount of cropland in cell	0.408	0.006	70.56	<0.0001
amount of cropland in cell squared	0.115	0.007	17	<0.0001
amount of pastureland in cell	0.996	0.013	76.34	<0.0001
amount of pastureland in cell squared	-3.164	0.016	-203.55	<0.0001
previous change in amount of pastureland in cell	-0.624	0.003	-196.67	<0.0001
previous change in amount of pastureland in cell squared	1.206	0.01	125.44	<0.0001
amount of pastureland in neighboring cells	0.428	0.002	254.09	<0.0001
amount of pastureland in neighboring cells squared	-0.038	0.0002	-156.37	<0.0001
Country: BDI	-0.523	0.015	-35.22	<0.0001
Country: BEN	-0.241	0.007	-35.51	<0.0001
Country: BFA	-0.054	0.004	-15.31	<0.0001
Country: BWA	0.299	0.003	108.63	<0.0001
Country: CAF	-0.11	0.003	-37.18	<0.0001
Country: CIV	-0.338	0.004	-80.72	<0.0001
Country: CMR	-0.14	0.004	-36.22	<0.0001
Country: COD	-0.198	0.003	-71.56	<0.0001
Country: COG	-0.216	0.005	-40.48	<0.0001
Country: COM	-0.202	0.109	-1.85	0.064
Country: CPV	0.017	0.06	0.28	0.782
Country: DJI	0.229	0.011	20.61	<0.0001
Country: ERI	0.162	0.006	27.53	<0.0001
Country: ETH	-0.026	0.003	-10.25	<0.0001
Country: GAB	-0.222	0.008	-26.61	<0.0001
Country: GHA	-0.024	0.005	-4.95	<0.0001
Country: GIN	-0.198	0.005	-42.91	<0.0001
Country: GMB	-0.536	0.026	-20.65	<0.0001
Country: GNB	-0.356	0.013	-27.61	<0.0001
Country: GNQ	-0.113	0.027	-4.19	<0.0001
Country: KEN	0.069	0.003	24.61	<0.0001
Country: LBR	-0.343	0.019	-18.07	<0.0001
Country: MDG	0.276	0.003	107.51	<0.0001
Country: MLI	0.123	0.003	47.44	<0.0001
Country: MOZ	0.105	0.002	43.28	<0.0001
Country: MRT	0.124	0.003	37.86	<0.0001
Country: MUS	-0.137	0.045	-3.02	0.003
Country: MWI	-0.044	0.005	-8.74	<0.0001
Country: NAM	0.275	0.003	109.5	<0.0001
Country: NER	0.1	0.003	33.05	<0.0001
Country: NGA	-0.05	0.003	-18.12	<0.0001
Country: RWA	-0.453	0.013	-35.27	<0.0001
Country: SDN	0.187	0.002	79	<0.0001
Country: SEN	-0.044	0.004	-9.94	<0.0001
Country: SHN	0.003	0.202	0.02	0.986
Country: SLE	-0.289	0.009	-31.57	<0.0001
Country: SOM	0.087	0.003	27.16	<0.0001
Country: SSD	0.042	0.003	14.19	<0.0001
Country: STP	0.606	0.101	6.02	<0.0001
Country: SWZ	-0.199	0.015	-13.44	<0.0001
Country: SYC	-0.81	0.637	-1.27	0.204
Country: TCD	0.162	0.003	62.72	<0.0001
Country: TGO	-0.131	0.007	-18.67	<0.0001
Country: TZA	0.086	0.002	35.54	<0.0001
Country: UGA	-0.308	0.005	-63.9	<0.0001
Country: ZAF	0.05	0.002	21.56	<0.0001
Country: ZMB	-0.134	0.003	-44.56	<0.0001
Country: ZWE	0.126	0.003	40.03	<0.0001

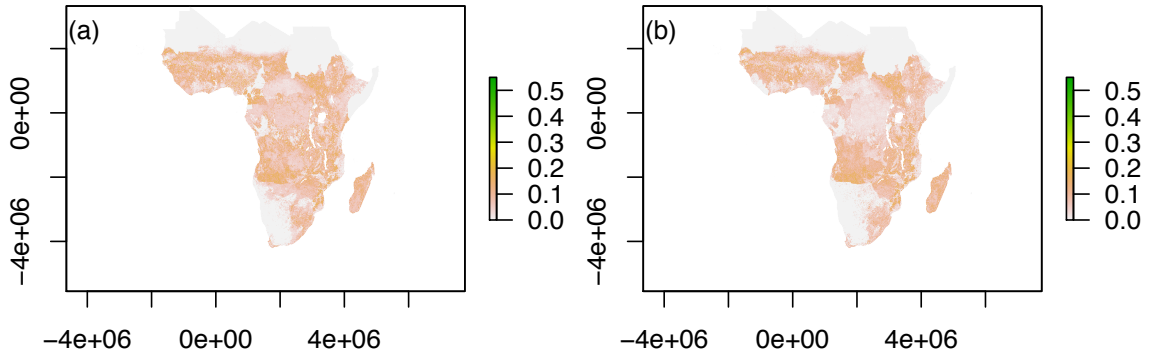
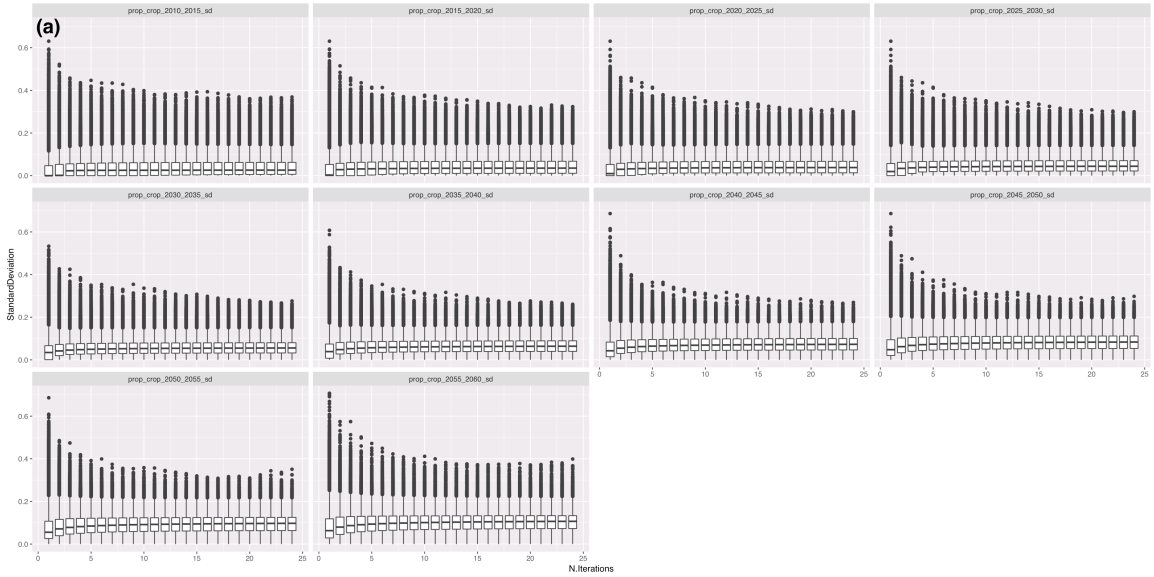


Figure S3. Standard deviation in (a) cropland and (b) pastureland extent for the Business-As-Usual scenario in 2060.



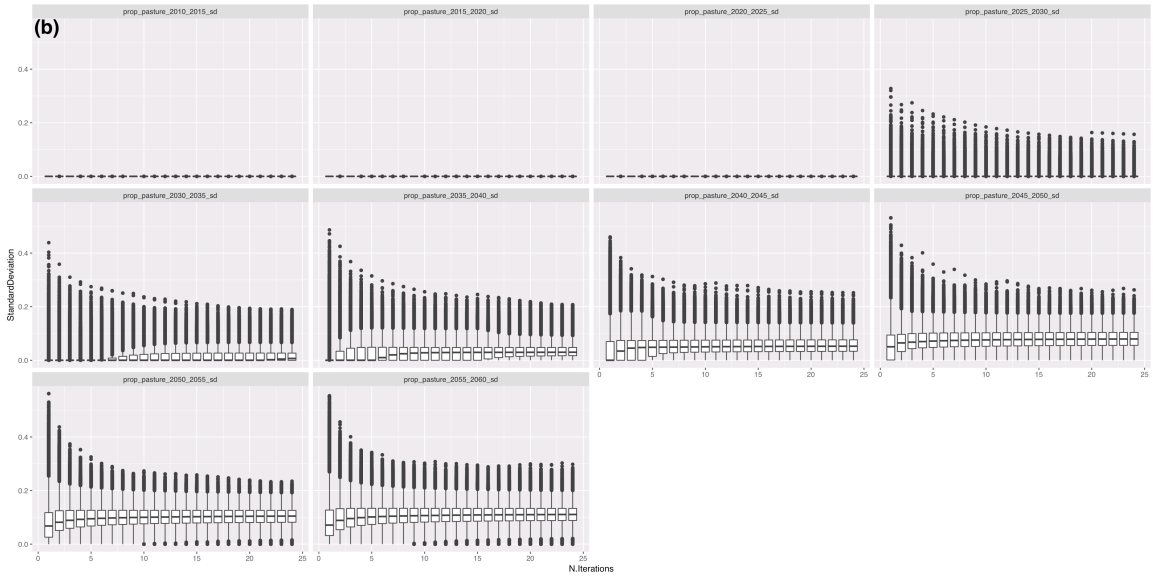


Figure S4. Standard deviation across different amounts of forecast iterations by cell for (a) cropland and (b) pastureland in Tanzania. Boxplots show 25th, 50th, and 75th percentiles, bottom and top of the vertical lines indicate 5th and 95th percentiles, respectively. Data was made by bootstrapping across a subsample of cells that experienced a change in agricultural extent 100 times. Other countries show similar results, with standard deviation of agricultural extent within a cell increasing until ~10-15 forecast iterations, and then remaining constant with larger numbers of model iterations.

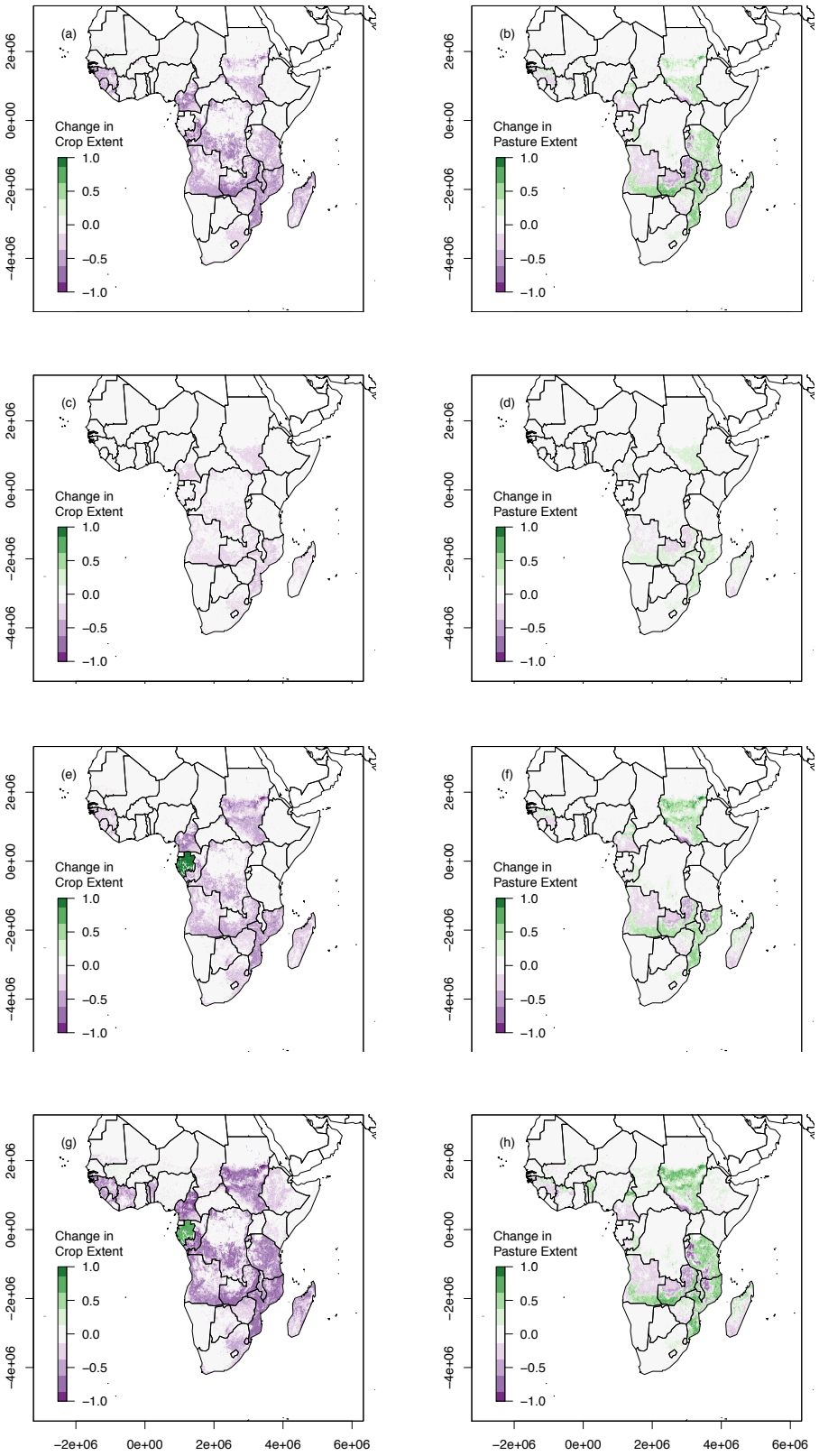

(a)
Change in
Crop Extent
(b)
Change in
Pasture Extent
(c)
Change in
Crop Extent
(d)
Change in
Pasture Extent
(e)
Change in
Crop Extent
(f)
Change in
Pasture Extent
(g)
Change in
Crop Extent
(h)
Change in
Pasture Extent
1.0
0.5
0.0
−0.5
−1.0
2e+06
0e+00
−2e+06
−4e+06
−2e+06
0e+00
2e+06
4e+06
6e+06

Figure S5. Projections of cropland (a,c,e,g) and pastureland (b,d,f,h) extent in 2060 for the yield (a,b), diet (c,d), trade (e,f), and combined (g,h) scenarios relative to projected agricultural extent in the BAU scenario. Difference in agricultural extent is measured as a proportion of a cell (e.g. 0.1 = 10% of the cell), where green indicates more agricultural land in the alternative scenarios than in the BAU scenario, and purple indicates less agricultural land in the alternative scenarios than in the BAU scenario. Countries in white were not included in the analysis.

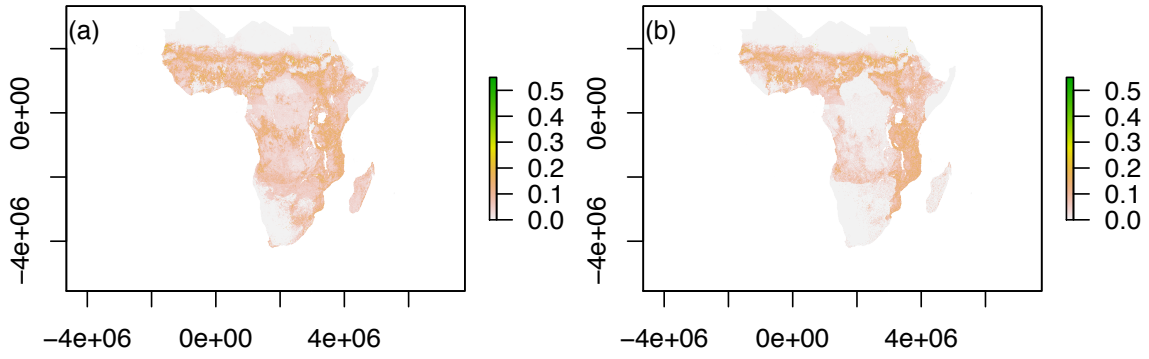


Figure S6. Standard deviation in (a) cropland and (b) pastureland extent for the yields scenario in 2060.

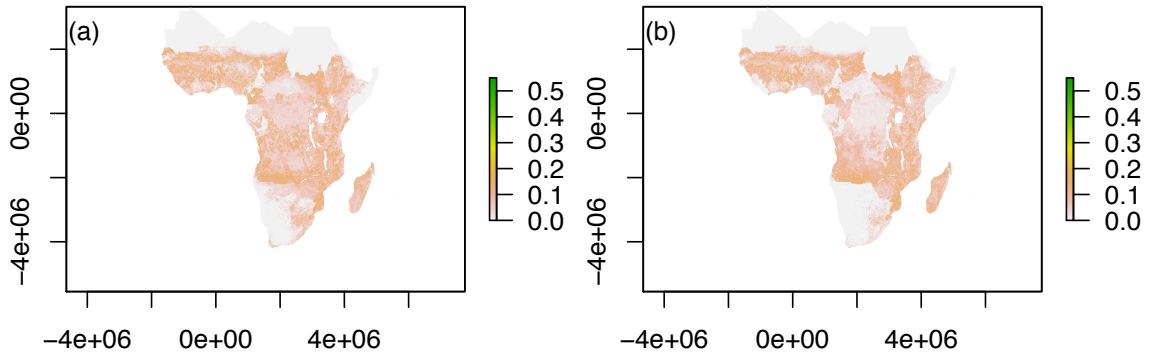


Figure S7. Standard deviation in (a) cropland and (b) pastureland extent for the diet scenario in 2060.

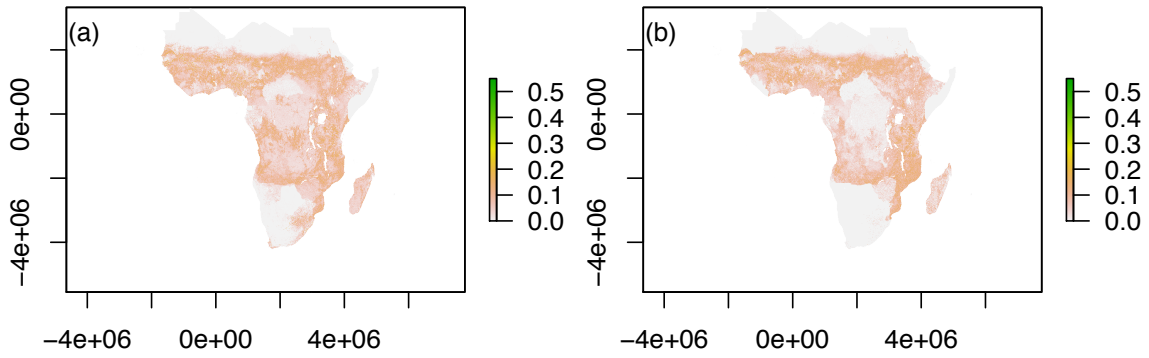


Figure S8. Standard deviation in (a) cropland and (b) pastureland extent for the trade scenario in 2060.

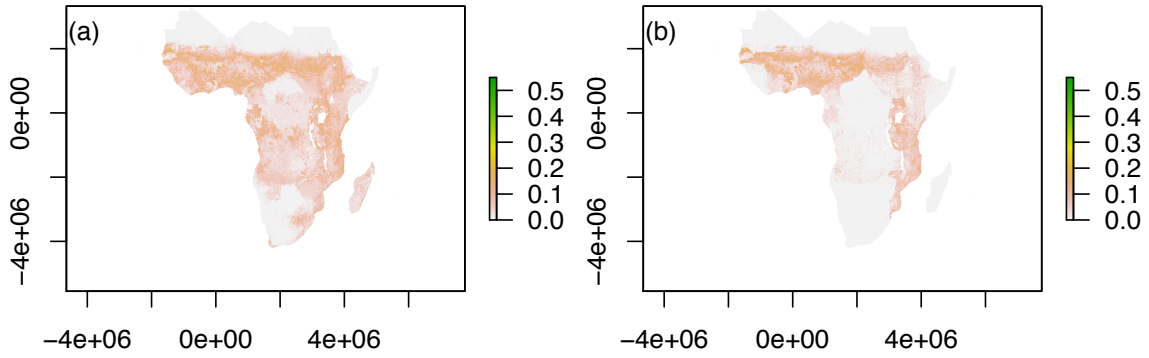


Figure S9. Standard deviation in (a) cropland and (b) pastureland extent for the all scenario in 2060.