Supplementary Information for: “Biodiversity effects of food system sustainability actions from farm to fork”

This document contains supplementary information for **“Biodiversity effects of food system sustainability actions from farm to fork.”**

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Appendix 1: Complete methods

The following appendix contains a complete description of the materials and methods to accompany the manuscript: "Biodiversity effects of food system sustainability actions from farm to fork," by Quentin D. Read, Kelly L. Hondula, and Mary K. Muth.

Notes on spatially explicit data

Spatial harmonization of county-level datasets: We used three datasets with values at the USA county (or county-equivalent) level: spatial boundaries (U.S. Census Bureau, 2014b), agricultural production data provided by the U.S. Census of Agriculture (U.S. Department of Agriculture, National Agricultural Statistics Service, 2014), and consumer expenditure data (U.S. Bureau of Economic Analysis (BEA), 2021). We harmonized the three datasets by spatially aggregating units where necessary to achieve a common set of counties across all three datasets. This required us to update the FIPS classification to the most recent scheme, then to aggregate Virginia's independent cities with their surrounding counties, as well as summing the production values for Aleutians East and West census areas in Alaska, which were separated in the expenditure dataset but not the production dataset.

Spatially explicit environmentally extended input-output models: In this manuscript, we used an EEIO model to estimate the total indirect and direct demand required to satisfy final consumer demand, and to derive the associated land requirements, making the model spatially explicit where possible. Any of the three components of an EEIO model (final demand, transactions among industries required to satisfy that demand, and environmental extensions) can be made spatially explicit (Sun et al., 2019). This can be done either by using endogenous spatially explicit data or by downscaling using an external spatial dataset. In this study, we used spatially explicit environmental extensions: crop production and land use at the county level, and biodiversity threat characterization factors at the ecoregion level. However, because county-level data are lacking, the final demand and transactions are not spatially resolved. We used values for the whole United States, downscaled by assuming that final demand across all demand categories for each county are proportional to the total income of that county. However, we do not present the results of the spatial downscaling of demand in the manuscript, but we retain the description of the methods here to facilitate potential later improvements to the values if better spatially resolved data for the final demand and transactions become available.

Production of agricultural and non-agricultural goods and consumption of food in each county

We derived data on agricultural production for the year 2012 for counties in the United States from the Census of Agriculture (U.S. Department of Agriculture, National Agricultural Statistics Service, 2014). We obtained production values, in 2012 dollars, for each of the 50 states and for the highest North American Industry Classification System (NAICS) code resolution available. In addition, we obtained land area used for the production of each crop and for pastureland in 2012. We aggregated the land area into annual cropland and permanent cropland, because the biodiversity characterization factors used later in the analysis to determine virtual biodiversity threat transfers are also divided up in this way.

State-level production: We obtained the County Business Patterns data for 2012 (U.S. Census Bureau, 2014a). The Census of Agriculture provides the total value of agricultural production and the total harvested area at the state level for a variety of four- and six-digit agricultural NAICS codes. We harmonized those NAICS codes with the relevant Bureau of Economic Analysis (BEA) codes. In most cases, there was a one-to-one or many-to-one correspondence between NAICS and BEA classifications; in the many-to-one case we could simply sum the production values for the multiple NAICS codes corresponding to one BEA code. However, there was one case of a one-to-many correspondence: the NAICS code classification for grain and oilseed production value is presented as a single aggregate value in the Census of Agriculture but corresponds to two BEA codes. To disaggregate the grain and oilseed production values, we used the state level crop sales data for the individual grain and oilseed crops. For industries other than those producing primary agricultural goods, e.g., food-processing industries such as cheese manufacturing (BEA code 311513) and snack food manufacturing (BEA code 311910), we obtained the total receipts of each industry in each state from the Statistics of U.S. Businesses data for 2012 (U.S. Census Bureau, 2015). These data are provided by NAICS code, typically six-digit resolution. We harmonized the NAICS classification with the BEA classification.

Downscaling state-level production to county level: We downscaled the state-level production data for each BEA code, including both agricultural and non-agricultural codes, to the county level. The number of establishments classified under each BEA code in each county was the variable we used to downscale state-level annual production values to county-level. We obtained the number of establishments in each county classified under agricultural NAICS codes from the 2012 Census of Agriculture, and the non-agricultural codes from the County Business Patterns data from 2012 from the U.S. Census Bureau. In each case we harmonized the NAICS classification with the BEA classification. We multiplied the state-level production data for each BEA code by the proportion of establishments in each county classified under that BEA code to yield the downscaled production values for each county.

Downscaling national consumption to county level: We obtained the 2012 personal consumption expenditure vector classified by the 411 BEA commodity codes for the USA from the BEA input-output data, and additionally obtained household income totals at the county level for 2012 (U.S. Bureau of Economic Analysis (BEA), 2021). Because of the lack of county-specific personal consumption expenditure data, we downscaled the national personal consumption expenditure vector to the county level by multiplying the consumption vector by each county's total personal income divided by the total income for the USA. Note: as mentioned above, due to the strong assumptions underlying the downscaling of national consumption to the county level, we do not present the estimates generated from the downscaling in the main manuscript or in the supplements (see "Notes on spatially explicit data" above). Instead, we present the estimates of consumption-side footprint summed across all counties to yield a total country-wide footprint; we retain the spatial disaggregation of the production-side footprint in our main results. However, the estimates for the spatial downscaling of the production-side footprints are available in our interactive data visualization (https://qdread.shinyapps.io/biodiversity-farm2fork/).

Total production required to satisfy final demand in each county: Producing the food to satisfy final consumer demand for food products requires the production of goods across all sectors of the economy to supply the industries that produce the goods directly purchased and consumed by households. An input-output model allows the estimation of the total production required to satisfy both the indirect and direct demand. The basic formulation of an environmentally-extended input-output model is given in Equation 1.

$$\mathbf{m} = \boldsymbol{B}(\boldsymbol{I} - \boldsymbol{A})^{-\mathbf{1}}\mathbf{f}$$

(Eq. 1)

Here, $\boldsymbol{A}$ is the direct requirements coefficients (DRC) matrix from the USEEIOv2.0 model (Yang et al., 2017); this matrix is derived from the make and use tables for 2012 supplied by the BEA. The DRC matrix represents, for each commodity produced, the intermediate requirements of all other commodities to produce one unit of output. The DRC matrix is generated by first normalizing the transactions in the make and use tables to produce a table of market shares of each industry for all commodities it produces (commodities $\times$ industries) and a table of the direct requirements of each commodity by each industry to produce its output (industries $\times$ commodities). Multiplying these two matrices results in the DRC matrix (commodities $\times$ commodities). This procedure is described in detail in (Miller and Blair, 2009). This method has been previously used to calculate the consumption of goods that drive land use under different scenarios (Zeng and Ramaswami, 2020). We took the Leontief inverse, i.e., $(\boldsymbol{I} - \boldsymbol{A})^{-1}$, of the DRC matrix and multiplied it by the downscaled final demand vector $\mathbf{f}$ for each county; the product $(\boldsymbol{I} - \boldsymbol{A})^{-\mathbf{1}}\mathbf{f}$ represents the total demand at the county level required to satisfy the final demand. In the following, we only consider the ten elements of the total demand vector representing primary agricultural goods: BEA code 1111A0, oilseeds and soybeans; 1111B0, wheat, corn, rice, and other grains; 111200, vegetables; 111300, fruits; 111400, greenhouse crops; 111900, all other crops (including peanuts and sugar crops); 112120, dairy cattle; 1121A0, beef cattle; 112300, poultry; 112A00, all other livestock. Code 114000, for wild-caught fish and seafood, is included in our final consumption results for completeness. However, because we only consider biodiversity threats due to terrestrial land use change, we do not account for any biodiversity impacts of wild-caught seafood (all excess demand for fish and seafood in alternative scenarios is assumed to be satisfied by expanded aquaculture rather than increased wild fish capture).

Food-related flows of goods between USA counties

We allocated the consumption footprint of agricultural goods to counties using the strong assumption that agricultural goods are transported from producer to consumer within the United States independently of the geographic distance between them. We assume that the consumption of goods in each county is directly proportional to the income of that county. In other words, all agricultural goods contribute to a common pool of goods that are drawn from by individual counties. Additionally this requires the assumption that the populations of all counties consume the same mix of foods, and that spending on food makes up an equal proportion of household budgets in all counties. Given these strong simplifying assumptions, we allocated a proportion of the total production of every individual county to be consumed by each county. We did this by taking the outer product of each county's production vector and the normalized county income vector. The result is a 411×3112 total consumption matrix for each county, including all primary agricultural goods required to produce the food consumed in that county, where each column is a vector with the production from a single county required to satisfy consumption in the target county.

Land use due to agriculture in each USA county

From the 2012 Census of Agriculture, we found the total land area devoted to each agricultural NAICS code and the total receipts of each NAICS code, at the state level, then converted the NAICS classification to the BEA classification using the method described above. The land area divided by the receipts is a land exchange factor representing the amount of land required to produce a dollar of output of each primary agricultural commodity in each state. We constructed a 3×10 satellite land exchange matrix for each state, corresponding to element $\boldsymbol{B}$ of Equation 1, where the rows represent the three agricultural land use types we considered (annual cropland, permanent cropland, and pastureland), and the columns represent the ten primary agricultural BEA commodity classifications that occupy agricultural land in the United States.

Food-related virtual land flows between USA counties and ecoregions

Estimating land flows between counties: For each county, we took the 10×3112 subset of its consumption matrix representing the consumption of primary agricultural goods sourced from each other county. The product of the 3×10 land exchange matrix and the 10×3112 consumption matrix is a 3×3112 matrix containing the land footprint of food consumption in each USA county, geographically resolved at the level of producing county.

Converting inter-county flows to ecoregion-to-county flows: We converted flows between counties to flows between ecoregions as follows. First, to divide the outgoing flows from counties among the ecoregions making up that county (many of the counties or county equivalents in the United States have more than one TNC ecoregion within their borders), we determined the proportion of cropland and pastureland pixels from the National Land Cover Dataset in each county that lie within each of the ecoregions that overlap with it. We weighted the outgoing annual and permanent cropland flows by the proportion of cropland pixels in each ecoregion (assuming that annual and permanent cropland are divided up by ecoregions in the same proportions), and the outgoing pastureland flows by the pastureland proportion. The result of this weighting is a vector of virtual land flows into each county from each TNC ecoregion.

Converting ecoregion-to-county flows to inter-ecoregion flows: Next, we divided the incoming flows to each county among its constituent ecoregions by finding the proportion of the county's population living within each ecoregion. We used the U.S. Census gridded demographic data product prepared by CIESIN (2017), with population totals at 30 arc-second pixel resolution for the United States in the year 2010 to generate the population estimates for the portion of each ecoregion intersecting with each county. The result of this second weighting is a vector of virtual land flows between each pair of TNC ecoregions. We did not use these flows in any further analysis but describe their calculation here for completeness.

Food-related virtual biodiversity threat transfers between USA counties

Technical background on biodiversity threat estimates: To estimate the virtual biodiversity threat transfers embodied in the virtual land transfers, we used biodiversity characterization factors developed by (Chaudhary and Brooks, 2018). The characterization factors represent the marginal number of species committed to eventual extinction for each additional 1 square meter of land converted from natural to human use in each Nature Conservancy ecoregion, assuming that the impact of land conversion does not vary spatially within an ecoregion. The characterization factor for a particular combination of taxon, human land use type, and ecoregion is a function of the following inputs: the original species richness of that taxon in the ecoregion; the habitat affinity, or the relative proportion of species richness lost from that taxon in that ecoregion when natural habitat is changed to a particular human land use type; the rate at which species richness increases as area sampled increases; and the vulnerability score for that taxon in the ecoregion, which essentially represents the proportion of endemic species in the ecoregion. Additional data required to estimate affinity values include the amount of natural habitat that has been converted into each human land use type in each ecoregion to date, and the number of species lost from the ecoregion as a result.

The theory underlying the characterization factors is based on the countryside species-area relationship (cSAR) (Pereira et al., 2014). Originally, ecologists observed a power-law relationship between land area and the number of species of a particular taxon found there, dubbed the species-area relationship (SAR). The power law takes the form $S = cA^z$, where A is the sampled area, S is the number of species encountered, and the parameter c is a constant that reflects the taxon's overall species richness. The power law exponent z typically varies around ¼, varying based on taxon, biome, and scale (Drakare et al., 2006). However, directly using the SAR power law to estimate potential extinctions in a region due to habitat loss may yield inflated estimates (He and Hubbell, 2013); direct use of the SAR implicitly assumes that when land is converted from natural to human use, it becomes completely hostile to life and cannot support any natural populations; of course, there are many possible human land uses with varying ability to support natural populations. Furthermore, different taxonomic groups have different affinities for human land use types. The countryside species-area relationship captures both those nuances to yield more reasonable estimates of potential extinctions when natural landscapes are affected by humans. When comparing the predictions derived from the cSAR to those derived from the SAR and another SAR-based approach, and validating all three against a database of bird extinctions in biodiversity hotspots, the predictions made by the cSAR model were a significantly better match to the observed data (Pereira et al., 2014).

A full description of the cSAR implementation from which we derive our biodiversity characterization factors is found in Chaudhary & Brooks (2018), including the data sources from which the parameters were taken. Following is a brief description of the model, paraphrasing Chaudhary & Brooks. The underlying cSAR model is given in Equation 2:

$$S_{loss,g,j} = S_{org,g,j}\Big(1 - \big(\frac{A_{new,j} + \sum_{i=1}^{16} h_{g,i,j} A_{i,j}}{A_{org,j}}\big)^{z_j}\Big)$$

(Eq. 2)

The subscript g refers to taxon (mammals, birds, amphibians, reptiles, and plants), the subscript i refers to land use type (there are 16, of which we only consider annual cropland, permanent cropland, and pastureland in this study), and the subscript j refers to ecoregion (804 globally, of which 86 are found within the contiguous United States, Alaska, and Hawaii).

In Equation 2, $S_{org,g,j}$ is the original number of species of taxon g in ecoregion j before human land use modification. A represents land areas within ecoregion j, where A_{org} is the original unmodified natural habitat area, A_{new} is the remaining unmodified area after human intervention, and A_i is the land area devoted to a particular human-modified land use type after intervention. $h_{g,i,j}$ is the affinity of taxon g to land use type i in ecoregion j. A value of h close to zero would indicate that land use type i is hostile to the taxon in that ecoregion and can support only very low species richness of that taxon, and a value of one would indicate no change in richness with land modification. A value above one would indicate that the modified landscape could support a higher richness than the unmodified. When averaging h values by taxon and land use type across all ecoregions, no values greater than one are present in the cSAR model parameters used in the present analysis (Chaudhary & Brooks 2018; Table 2). Finally, z_j is the species-area relationship exponent for the ecoregion; typically, values of z range around 0.25. Therefore, if the original species richness, the extent of modified land, the taxon affinities, and the SAR exponent are known, this equation results in the expected number of species ultimately committed to extinction within the ecoregion given that land use. Details of how the parameters S_{org}, A, h, and z were derived are found in Chaudhary & Brooks (2018).

The cSAR formulation is used to derive characterization factors (CFs) that express potential biodiversity damage as a rate of global species extinctions per square meter of land use converted to a particular land use in a particular ecoregion for a particular taxon. This requires first converting the species loss to a marginal rate and then deriving a global extinction rate from the ecoregion-specific extinction rate, as follows. First, an allocation factor $a_{g,i,j}$ is calculated for each taxon g across each land use type i in each ecoregion j as given in Equation 3. The allocation factors for a particular taxon in a particular ecoregion sum to 1 and indicate the share of regional extinctions due to each type of land conversion.

$$a_{g,i,j} = \frac{A_{i,j}(1 - h_{g,i,j})}{\sum_{i=1}^{16} A_{i,j}(1 - h_{g,i,j})}$$

(Eq. 3)

Next, a regional land-occupation characterization factor $CF_{regional,occ,g,i,j}$ is calculated for each taxon g across each land use type i in each ecoregion j. This represents the projected number of species of taxon g committed to local extirpation in ecoregion j for each unit area of land use type i (Equation 4).

$$CF_{regional,occ,g,i,j} = \frac{S_{loss,g,j}\, a_{i,j}}{A_{i,j}}$$

(Eq. 4)

The regional characterization factor is converted to a global characterization factor by multiplying by the vulnerability score $VS_{g,j}$, or the weighted proportion of the range of each species in taxon g that occurs in ecoregion j, derived from IUCN range maps, with an additional weighting factor applied representing the IUCN category of extinction risk (Equation 5). For example if 100% of species in taxon g are completely endemic to ecoregion j and are listed as critically endangered by the IUCN Red List, they will all go globally extinct if they are locally extirpated from ecoregion j ($VS = 1$). Details of the derivation of VS are provided in Chaudhary et al. (2015).

$$CF_{global,g,i,j} = CF_{regional,occ,g,i,j} * VS_{g,j}$$

(Eq. 5)

These global characterization factors are used in our further analysis. They are expressed in units of species potentially committed to global extinction per square meter. Within each ecoregion, there are a number of characterization factors: one for each combination of biological taxon (plants, mammals, birds, amphibians, and reptiles) and agricultural land use type (annual cropland, permanent cropland, and pastureland). We present the characterization factors associated with land occupation and medium land use intensity in all cases. We reran the analysis with the low-intensity and high-intensity characterization factors and found that the median sensitivity of the species extinction threat totals for each combination of land use type, taxon, and scenario was 1.5% for medium versus low intensity, and 0.4% for medium versus high intensity. Because of the relatively low sensitivity and because of the lack of nationally available data to distinguish between levels of land use intensity, we chose to use the medium-intensity factors. We used the factors for land occupation rather than land transformation because we are dealing with land that has already been transformed to agricultural use and our alternative scenarios involve a contraction of this land area rather than any new expansion.

Conceptual issues regarding the biodiversity threat estimates: The biodiversity threat estimates we generated here represent the number of species committed to extinction by agricultural land use in the United States. Although few plant and vertebrate species have been conclusively proven to have gone globally extinct due to agricultural land transformation in the United States, the current level of agricultural land use has reduced the available habitat so much for some species that they cannot maintain a non-negative population growth rate in the long term. Therefore, they are inevitably committed to extinction if current trends continue. However, reducing the land area devoted to agriculture would allow natural habitats to regenerate over time, possibly allowing population growth rates to recover.

Here, biodiversity threat is expressed in units of potential global species extinctions per meter squared of land converted from natural land to food production. This translates all activities related to food production to a single common metric that can be compared across geographical regions. The cSAR approach is a "top-down" approach that calculates losses at the level of taxonomic groups rather than a "bottom-up" approach that estimates impacts at the level of individual species before summing them up to find the total impact. Therefore, it is less data-hungry than other potential candidate methods. However, it suffers from a few limitations. First, because threats are expressed in absolute number of species extinctions, if results are summed across taxa, they will be weighted toward the taxon with the highest species richness. Because we used characterization factors for plants and several vertebrate groups, and plants have a much higher species richness than vertebrates, around 75% of the species extinctions we predict in the baseline case are plants. Second, because the units are global extinctions, it tends to ignore local impacts in areas that have low endemism. In fact, for a few of the ecoregions that have relatively low endemism, threat is shown to be negligible or zero, though that might not be the case considering local or regional extinctions.

Calculation of biodiversity threat transfers: We joined all the ecoregion-to-county virtual land flows (estimation of these flows is described in the section above titled "Food-related virtual land flows between USA counties and ecoregions") with the characterization factors for the exporting ecoregion. The product of the land flow in square meters and the characterization factor represents the number of species committed to extinction by ongoing agricultural land use in the exporting ecoregion that contribute to the importing county's biodiversity threat footprint due to food consumption. We used the population weights described above to convert the pairwise virtual biodiversity threat transfers between ecoregions to pairwise transfers between counties.

Virtual land and biodiversity threat transfers due to imported agricultural goods

Foreign food imports contribute substantially to the global land and biodiversity footprint of U.S. consumers. To address this, we compiled and/or derived the following data from FAOSTAT (FAO (Food and Agriculture Organization of the United Nations)), 2021): food production in all countries that are agricultural trading partners with the United States, the proportion of those countries' food production that is exported to the United States, the harvested land area of each crop, and the proportion of crops grown for feed and pastureland that are used to feed livestock eventually exported to the United States.

Virtual land transfers due to imported crops: First, we averaged the most recent five years of data for the relevant FAOSTAT data series, all at the country level: production in tons and area harvested for each crop, food balance sheets including the proportions of each crop used for feed and human consumption, export data reported by the United States' trading partners, land use inputs data including total amount of pastureland, and livestock patterns data including the total amount of livestock in each major species converted to common biomass-based units. We harmonized the commodity codes in the crop and livestock production dataset with those in the trade dataset. We joined the crop production dataset with the trade dataset and multiplied the total area harvested for each crop in each country by the proportion of that crop's production that is exported to the United States. We summed these values across annual and permanent crops within each exporting nation. This represents the virtual annual and permanent cropland transfers due to directly exported crops.

Virtual land transfers due to imported animal products: For virtual land transfers embodied in animal products, the calculation is more complex because it requires estimating the pastureland footprint for grazing animals as well as the land used to grow feed for the animals. We made a number of simplifying assumptions. First, we joined the food balance sheet for each crop in each country with the crop production, crop trade, and area harvested data for those countries. The product of the proportion of each crop that is used for feed times the area harvested is the land area of each crop used to feed animals in each country. Next, we joined an additional dataset: the livestock patterns dataset, which presents the amount of each major type of livestock (excluding smaller types such as honeybees, turkeys, rabbits, etc.) in each country in biomass-equivalent units. We multiplied the total annual and permanent cropland footprint associated with animal feed in each country by the relative share of the livestock patterns for each major livestock type. This resulted in the annual and permanent cropland footprint used to feed each livestock species in each country, assuming for simplicity that all livestock species receive the same mix of crops as feed.

We additionally joined the livestock patterns dataset with the land inputs dataset, including the area of pastureland in each country. We multiplied the total pastureland in each country by the relative share of the livestock patterns for each major livestock type, this time including only ruminant grazers that use pastureland. This resulted in the pastureland footprint used to feed each grazing livestock species in each country. The livestock patterns dataset also includes the amount of livestock for each species in each country used to produce meat, milk (for ruminants), and eggs (for chickens). We multiplied the land footprints for each species by the proportion of stock used to produce each type of product, resulting in the annual and permanent cropland footprint associated with meat, dairy products, and eggs for each species. Finally, we derived conversion factors to estimate the approximate weight of milk required to produce a unit of butter or cheese. We averaged the conversion factors provided by FAO (FAO (Food and Agriculture Organization of the United Nations)), 1972) and ERS (USDA Economic Research Service, 2021); we used the average of the conversion factors for all dairy products as the factor for the "other dairy" category in the FAOSTAT food export dataset. We used the conversion factors to disaggregate the milk cropland footprints into footprints associated with each dairy product specifically.

Finally, we joined the cropland and pastureland footprints associated with all exported animal product from all countries exporting to the United States with the trade data and multiplied the animal-derived land footprints with the proportion of each animal product exported to the United State from each other country. This results in the virtual land transfer, of each major land type, embodied in animal products exported from foreign countries into the United States.

Virtual biodiversity threat transfers from foreign countries: We proportionally allocated the virtual land flows from exporting countries to ecoregions within those countries. First, we counted the pixels in the global cropland and pastureland layers in each intersected country-ecoregion polygon. We used these counts to determine the proportion of cropland and pastureland in each country that lies within each of its ecoregions. Assuming the same proportional division of annual and permanent cropland, we divided the virtual land flows originating from each country among the ecoregions within it, weighted by the relative proportions of pixels from the global cropland mask layer (Thenkabail et al., 2016) and pastureland layer (Ramankutty et al., 2010) within each of a country's ecoregions. To estimate the virtual biodiversity threat transfers associated with the virtual land transfers, we used the characterization factors published by Chaudhary and Brooks in the same way as above, then summed the transfers from each ecoregion back up by exporting country.

Alternative consumption scenarios: diet shifts and food waste reduction

We modeled the effects of nationwide diet shifts and food waste reduction on the land footprint of agricultural production and consumption in the United States, and associated implications for biodiversity threats. Note that these alternative scenarios do not account for costs or other issues in transitioning to different diets or to a food system with greatly reduced waste; instead, we simply assume that the changes occur instantaneously. Furthermore, the biodiversity threat reduction relative to the baseline scenario is calculated assuming that land taken out of agricultural production can immediately support the same number of species as previously undisturbed land (i.e., no hysteresis and no time lag to full recovery). However, a meta-analysis of ecosystem recovery studies documented only partial recovery of pre-disturbance diversity for recovering agricultural land after roughly 20 years (Moreno-Mateos et al., 2017). In addition, we do not account for wild populations' potential to adapt to agricultural habitats (i.e., affinity of taxa to a particular land use type is constant). Therefore it is more appropriate to consider the alternative scenarios as counterfactual cases rather than a simulation of a process occurring over time.

The alternative diets we consider are the Planetary Health diet proposed by the EAT Lancet Commission (Willett et al., 2019) and the three healthy dietary patterns presented in the United States' 2020-2025 dietary guidelines (U.S. Department of Health and Human Services and U.S. Department of Agriculture, 2020). While both diets attempt to deliver balanced, healthy nutrition, the Planetary Health diet explicitly considers sustainability and minimizing land footprint in its formulation; in contrast, the three USDA-recommended diets only consider the individual's health and not environmental sustainability. The daily allowance of meat on the Planetary Health diet is much lower than the current average meat consumption in the USA. Dairy products, added fats (any fat added during processing or cooking, such as cooking oils), and added sugars are also allocated fewer calories than currently consumed. In contrast, calories from fruits, grains, nuts, and vegetables are higher than the current USA consumption. While all three of the USDA-recommended diets have fewer calories due to meat and added fats than the current average American eats daily, they compensate for this with a substantially increased dairy consumption, in addition to increases in the fruit, grain, and vegetable food groups. In further contrast to the Lancet diet, the USDA-recommended diets allocate roughly the same or slightly more calories per day to added sugars as the current typical American level of consumption.

To simulate the effects of food waste reduction, we separately assumed a 50% reduction in avoidable pre-consumer food waste (including retail waste but excluding on-farm and manufacturing waste) and a 50% reduction in avoidable consumer food waste (including household and food service waste). In summary, our analysis included five distinct diet scenarios: the baseline and four counterfactual diet scenarios (Planetary Health diet and the three USDA diets) and four waste scenarios (the baseline, 50% pre-consumer waste reduction, 50% consumer waste reduction, and 50% reduction in both pre-consumer and consumer waste). We did a full-factorial cross of the diet and waste scenarios, resulting in 20 scenarios total. Note that we only present the baseline and full waste reduction scenarios in the manuscript, for a total of 10 scenario combinations; the methods for all waste scenarios are presented here for completeness.

To determine the projected consumption of agricultural goods across the different scenarios, we needed to (1) harmonize the food group categories from both the Planetary Health and USDA diets with the food categories in the USDA's Loss-Adjusted Food Availability (LAFA) dataset from which we obtained the food waste rates for 2012 (using years as close to 2012 as possible for those food items that did not have data for 2012 available) and then (2) convert the daily food group servings values to common units (cal/day). First, we manually constructed a crosswalk table to harmonize the food group categorizations from the two diets with the list of food categories in the LAFA dataset. Because the LAFA categorization is much finer than the food group categorization for any of the recommended diets, this entailed many-to-one mapping of LAFA categories to diet categories. The exceptions to this are that the diet categories distinguish between whole and refined grains, and between saturated and unsaturated fat, while LAFA does not; those categories were aggregated for our harmonized classification. Next, we converted the daily food group allowances to calories per day by using the per capita food availability in the LAFA dataset, which presents availability in a variety of different units for each food and facilitates conversion to calories. Finally, we used the "retail to consumer" food waste rate from LAFA to represent pre-consumer waste, and used the "edible consumer" food waste rate for the consumer stage. We calculated the reduction in production that would result from 50% reduction in food waste at both of these stages, assuming that if waste is reduced, production reduces by the amount needed to satisfy the new reduced amount of consumption.

Potential changes in virtual land and biodiversity threat transfers in the alternative scenarios

To estimate possible changes to land and biodiversity footprints of food production and consumption under the alternative scenarios, we applied the scenario factors for each BEA code to the baseline food consumption final demand vector to generate 19 alternative final demand vectors in addition to the baseline. Again the 20 scenarios are a full factorial cross between four waste scenarios (baseline, 50% pre-consumer waste reduction, 50% consumer waste reduction, 50% waste reduction across both sectors) and five diet scenarios (baseline, Planetary Health, USDA/DHHS Dietary Guidelines US-style, USDA Mediterranean-style, and USDA vegetarian). We applied the same procedure as described above for the baseline final demand vector to estimate the total direct and indirect demand for primary agricultural goods in each county. To operationalize the assumption that all excess demand for seafood above baseline (summing across direct consumer demand and indirect demand via processed products containing seafood), we found the difference between total demand for BEA code 114000 (wild-caught fish) in the alternative scenario versus the baseline scenario. If this difference was greater than zero, we reassigned that amount of demand to BEA code 112A00 (animal farms and aquaculture). Next we continued with the procedures as described above to estimate the proportional allocation of production to consumption based on population, the land footprints associated with the consumption, and finally the biodiversity threats associated with the land footprints. We also applied the same procedure to estimate foreign imports of land and biodiversity threats in the alternative scenarios.

Key assumptions

Unfortunately, the data sources we used for this analysis do not have any quantitative uncertainty associated with them. Therefore, it is difficult to determine how sensitive our final results are to uncertainty in the underlying data. The exception is the biodiversity characterization factors provided by Chaudhary & Brooks (2018), who provided a low, medium, and high intensity value for each characterization factor. As we describe above, we performed a sensitivity analysis and found that the median difference in total biodiversity threat estimates by region was negligible. Here, we outline the most important assumptions we made in the modeling exercise.

Assumptions: Baseline waste rates

- We assumed that no losses before the retail stage were avoidable waste, and thus that no pre-retail food loss was addressable by waste reduction interventions. This is a conservative assumption: many interventions have been proposed or partially implemented to reduce on-farm food loss, as well as waste during the manufacturing and processing stages (Muth et al. 2019).
- We inherit all assumptions made in the estimation of the loss factors from the USDA Loss-Adjusted Food Availability (LAFA) data series. Most of these loss factors are broadly extrapolated from a small number of data points across many food groups and contexts. In many cases, loss factors have been assumed to be constant since they were first estimated several decades ago, although loss rates may have changed significantly since then. The LAFA data series comprises the best available estimates of food loss and waste at the national level for the USA, and therefore are widely used in analyses like this one. Improving the quality of the loss factors would provide a more accurate picture of the potential benefits of waste reduction.

Assumptions: Domestic land footprint

- The indirect demand required to satisfy final demand is uniform across the country. In other words, a final consumer product requires the same inputs to produce regardless of where it is produced or consumed.

- All individuals in the United States spend an equivalent proportion of their income on food, and consume the same average diet. Therefore the only variation in consumption land footprint across counties is from the variation in total consumer spending by county, which is a function of the population and affluence of the county.
- Total land area harvested per crop at the state level can be downscaled to the county level by the relative numbers of establishments for that crop's NAICS code at the county level.
- The yield of a crop measured in monetary value per land area is the same for all counties in a state.
- All consumers in the United States consume an equal mix of goods sourced from everywhere in the United States and world, completely independent of the geographic location of the consumer. This is a strong assumption but does not affect the main findings which are summed across all consumers.
- The only consumption of agricultural goods that we consider for the land footprint is final consumer demand by households, as captured by the personal consumption expenditure totals in the BEA input-output data. This ignores, e.g., government purchases of food.
- All pastureland is actively used. This assumption derives from our calculation of land exchange factors by state as the quotient of total pastureland area and monetary output of grazing animals. This assumption was not as strong for cropland because in that case the numerator is area harvested, implying active land use.
- We further assumed that all agricultural land has a single use, although it is possible that some land may be used for both animal forage and food crops. Any such land would be double-counted, potentially overestimating the land footprint.

Assumptions: Foreign land footprint

- We use the export values reported by the United States' trading partners (because they are more likely to be comparable to the total production quantities for those countries) rather than import values reported by the United States, though the two differ.
- The foreign land footprint may be exaggerated relative to the domestic because it is not possible to disaggregate exports destined for household consumption from other exports. Therefore, the foreign footprint has a slightly wider boundary than the domestic one. Furthermore, note the other methodological differences between the estimation of domestic and foreign land footprints (see above) when comparing the two.
- All livestock in a particular country consume the same mixture of feed crops. The apportioning of total crop quantity used for animal feed among livestock species was done purely based on the biomass of each livestock species, not accounting for differences in diet among livestock species.
- Livestock are either used for meat production, or milk/eggs production, but not both. This may overestimate the land footprint because in reality some individual animals may produce multiple products.
- All pastureland in foreign countries is actively used. As in the domestic analysis, we account for the fact that not all cropland is actively harvested each year, but do not have analogous data allowing us to account for this in the case of pastureland. This may lead to overestimation of the pastureland footprint.
- As in the domestic analysis, we assumed that agricultural land has a single use, ignoring any potential multiple use of the same land for producing animal forage and food crops.
- The values for cropland and pastureland used to produce animal products for export depend on the conversion factors that underlie the FAOSTAT livestock patterns dataset, as well as the dairy conversion factors we derived from FAOSTAT and USDA ERS.
- The FAOSTAT livestock patterns dataset only includes the most numerous livestock species (asses, buffaloes, camels, cattle, chickens, goats, horses, mules, pigs, and sheep), ignoring less common species. Therefore we assume that the land footprint of imported livestock production of less common species is negligible.
- The portion of output exported to the United States has the same land footprint by weight as the rest of the output.

Assumptions: Domestic and foreign biodiversity footprint

We inherit all assumptions made by Chaudhary and Brooks (2018) when developing the biodiversity characterization factors. See Table 1 in Chaudhary and Brooks (2018) for a list of the data sources used in the calculation of the characterization factors.

- The most important of these assumptions is that the countryside species-area relationship holds, and that it is possible to derive a marginal extinction per square meter of land that is relatively consistent across the range of land use values we present here. In other words the slope of the relationship does not change substantially over the range we are considering).
- Once we assume that cSAR is a valid foundation, the biodiversity threat model yielding the characterization factors has numerous parameters and may be more or less sensitive to the literature-derived values for those parameters. This includes the habitat affinity values for taxon/land use/ecoregion combinations, and the endemism proportions used to convert local extinction threats to global.
- The parameter h (habitat affinity for each taxon for each land use type in each ecoregion) was a function of three inputs: the broad habitat affinity taken from the IUCN habitat classification scheme (five classes), a relative richness parameter taken from a meta-analysis by Newbold et al. (2015) for vertebrate taxa and from a meta-analysis conducted by Chaudhary et al. (2016) for plants, and the species-area power law exponent for each taxon taken from a study by Drakare et al. (2006). The relative richness parameter was used to derive habitat affinities for a finer classification of land use than the coarse five classes in the IUCN scheme.
- Furthermore, the biodiversity threat reduction relative to the baseline scenario is calculated assuming that land taken out of agricultural production can immediately support the same number of species as previously undisturbed land (i.e., no hysteresis and no time lag to full recovery).
- We assume that there is no cost of time or resources required to restore agricultural land to natural habitat capable of supporting the same level of biodiversity as undisturbed habitat.
- Finally, our approach also assumes that wild populations of organisms do not adapt to agricultural landscapes, meaning that their affinities to different land use types remain constant over time.

Code and data availability

All code required to reproduce the analyses described in this paper is contained in a permanent copy of a GitHub repository on Zenodo (GitHub link https://github.com/qdread/biodiversity-farm2fork-analysis; permanent Zenodo DOI https://doi.org/10.5281/zenodo.5949590). Data required to reproduce the analysis is archived on a Figshare repository (https://doi.org/10.6084/m9.figshare.14892087). View our interactive data visualization app at https://qdread.shinyapps.io/biodiversity-farm2fork/.

Appendix 2: Supplemental figures

This appendix contains supplemental figures for the manuscript "Biodiversity effects of food system sustainability actions from farm to fork" by Quentin D. Read, Kelly L. Hondula, and Mary K. Muth.

Please note that not all possible visualizations of data and model results are presented in this document. To interactively view results and generate tables, plots, and maps, please visit the Shiny app accompanying this manuscript at https://qdread.shinyapps.io/biodiversity-farm2fork.

Figure S1. Methods graph

This figure graphically shows the relationship between each component in our data synthesis and modeling procedure. Each cluster (blue box with rounded corners) represents a phase of the data synthesis and modeling. Within each cluster, green boxes represent data sources incorporated in that phase, and red boxes represent models used in that phase. In each scenario, the food consumption data are derived from the USDA LAFA dataset, modified by the appropriate set of diet shift and waste reduction scenario parameters. Food consumption determines the required levels of domestic and foreign production (the USEEIO input-output model is used to estimate domestic production, and FAOSTAT trade and production data are used directly for foreign production). Next, the land exchange tables we developed are used to convert domestic production to domestic land footprint, and FAOSTAT yield and food balance sheet data are used for the foreign land footprint. We used the Chaudhary & Brooks model parameterized with IUCN and WWF data to convert the land footprints to biodiversity footprints for each scenario.

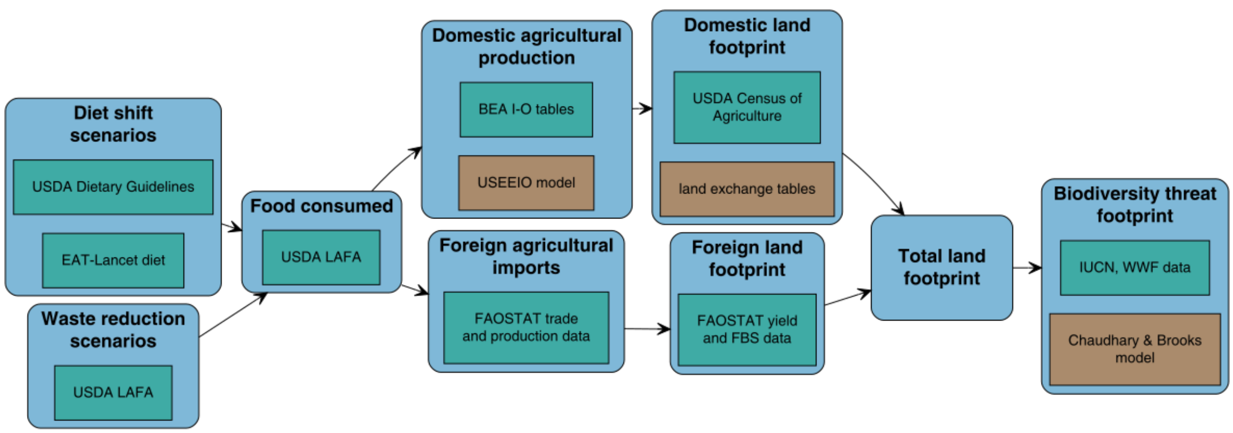

Figure S1: Data sources and models used in the study

Figures S2-S3. Summary maps

Figures S2 and S3 show global ecoregions colored by WWF realm in the United States and across the entire world respectively.

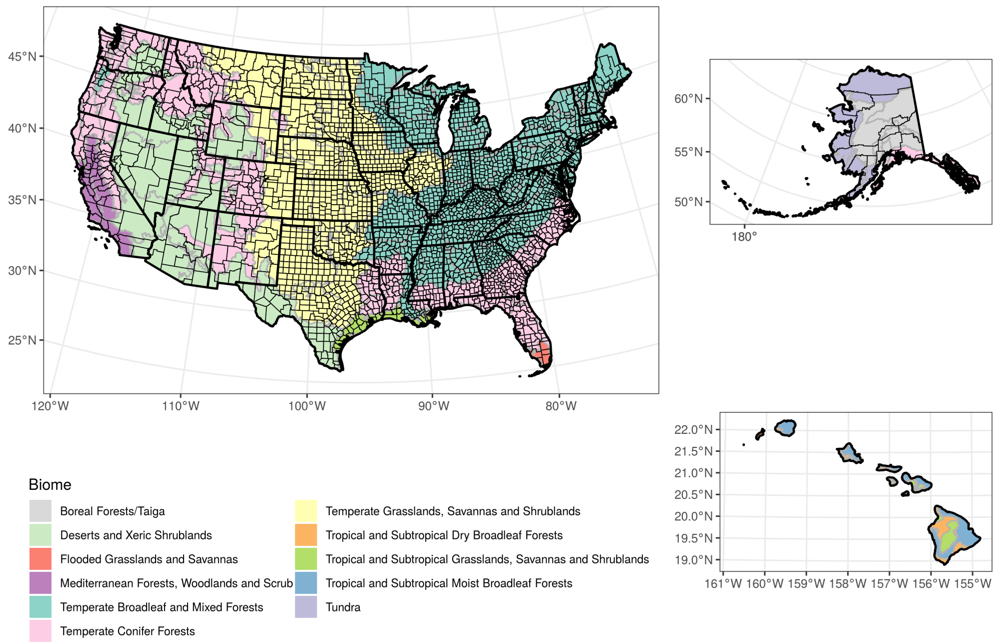

Figure S2: United States map showing global ecoregions categorized by realm

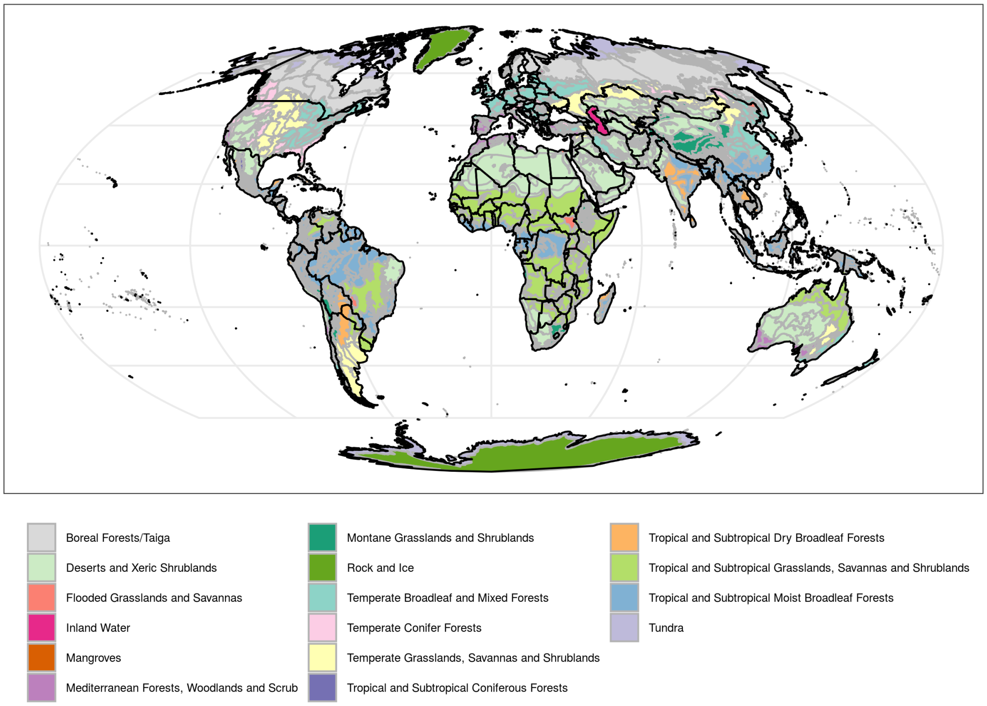

Figure S3: World map showing global ecoregions categorized by realm

Figure S4. Disaggregated production totals

This figure shows the total production, in units of value (billion USD), of each type of domestically produced primary agricultural good in each scenario (in contrast to Figure 2 in the main text, which shows the same values divided by the baseline consumption). Bars representing plant-derived goods are shaded in green, and bars representing animal-derived goods are shaded in pink. Each panel represents a different combination of diet scenario (baseline, three USDA diets, and planetary health diet) and waste scenario (baseline and 50% reduction). *Note*: A similar accounting is not possible for agricultural goods imported from foreign countries because of the different methodology and underlying data used for foreign imports.

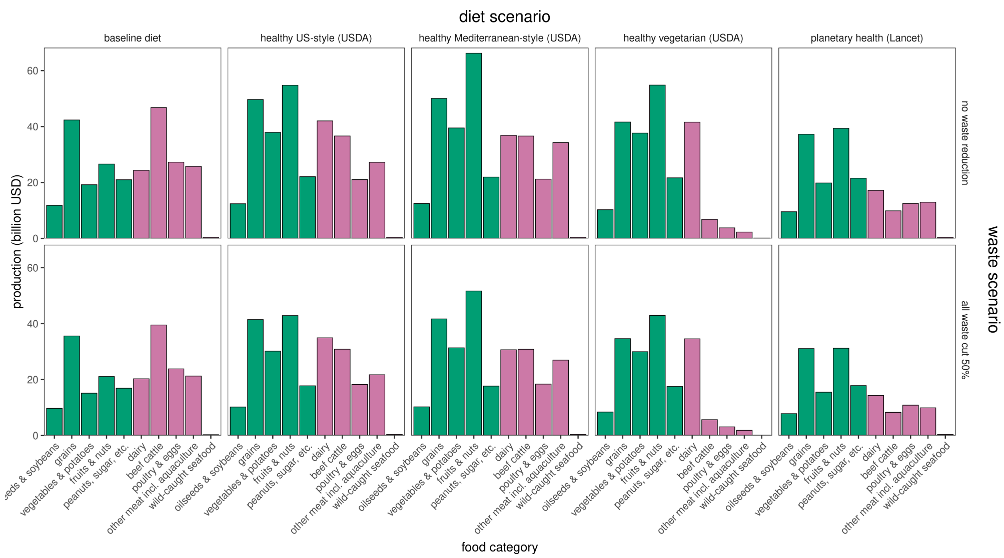

Figure S4: Total consumption of each primary domestic agricultural good in each scenario, by value

Figure S5. Disaggregated virtual land footprints

This figure shows the virtual land footprint of food consumed in the United States in the baseline scenario and alternative diet and waste scenarios, disaggregated by domestic (blue shading) versus foreign origin (orange shading), with separate totals for annual cropland, pastureland, and permanent cropland. The bars represent total amounts of land virtually consumed in the United States each year, in units of square kilometers per year. Each panel represents a different combination of diet scenario (baseline, three USDA diets, and planetary health diet) and waste scenario (baseline and 50% reduction).

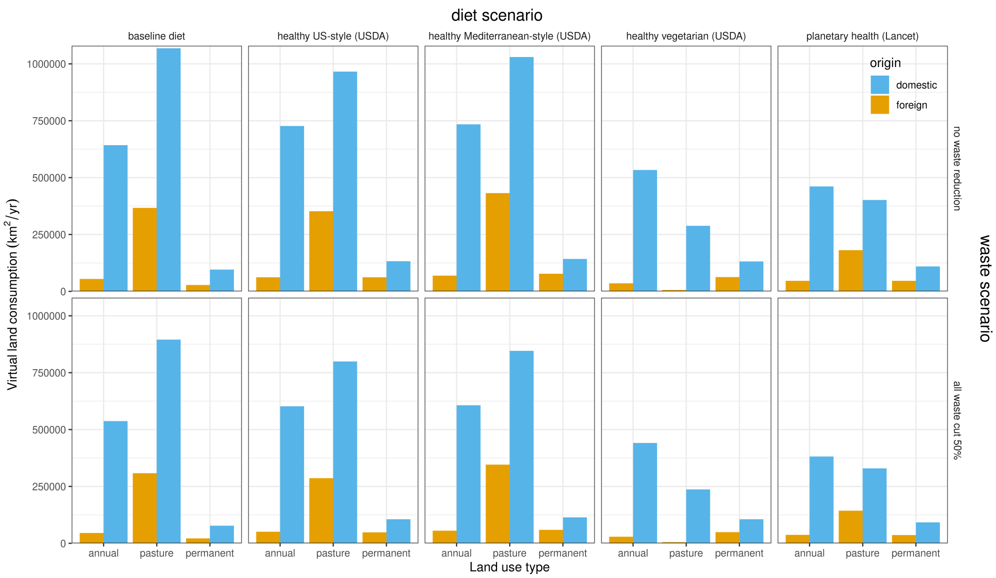

Figure S5: Total virtual land consumption in each scenario, by origin and land type

Figures S6-S12. Disaggregated virtual biodiversity threat footprints

The following figures show the virtual biodiversity threat footprints for the baseline case and the alternative diet and waste scenarios, disaggregated by origin, land use type, and taxon. In all these figures, the heights of the bars represent the number of terrestrial species forecast to eventually become globally extinct due to land used to produce food consumed in the United States. The biodiversity threat footprints are disaggregated by origin (blue shading represents domestic origin and orange shading represents foreign origin) and by land use type. Each panel of each figure represents a different combination of diet scenario (baseline, three USDA diets, and planetary health diet) and waste scenario (baseline and 50% reduction). Figure S6 shows the values for all taxa summed, Figure S7 shows plants only, Figure S8 shows all animal taxa summed, Figure S9 shows amphibians, Figure S10 shows birds, Figure S11 shows mammals, and Figure S12 shows reptiles.

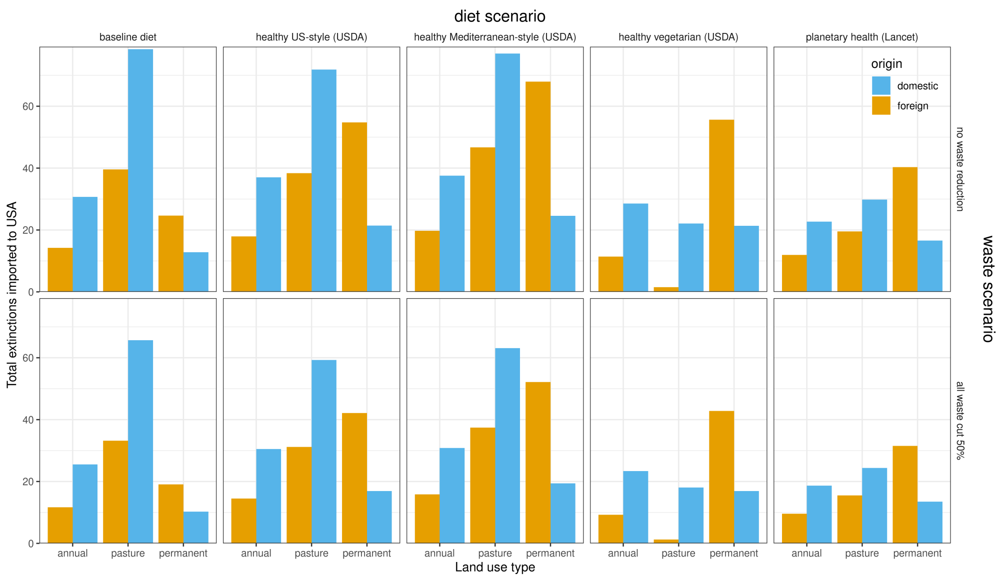

Figure S6: Total virtual biodiversity threat footprint in each scenario, by origin and land type: all taxa summed

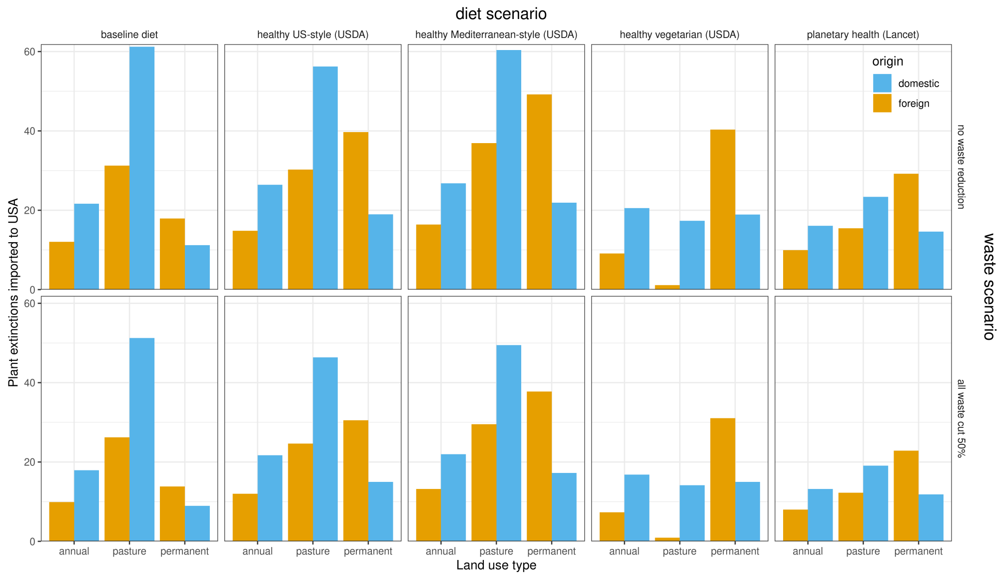

Figure S7: Total virtual biodiversity threat footprint in each scenario, by origin and land type: plants

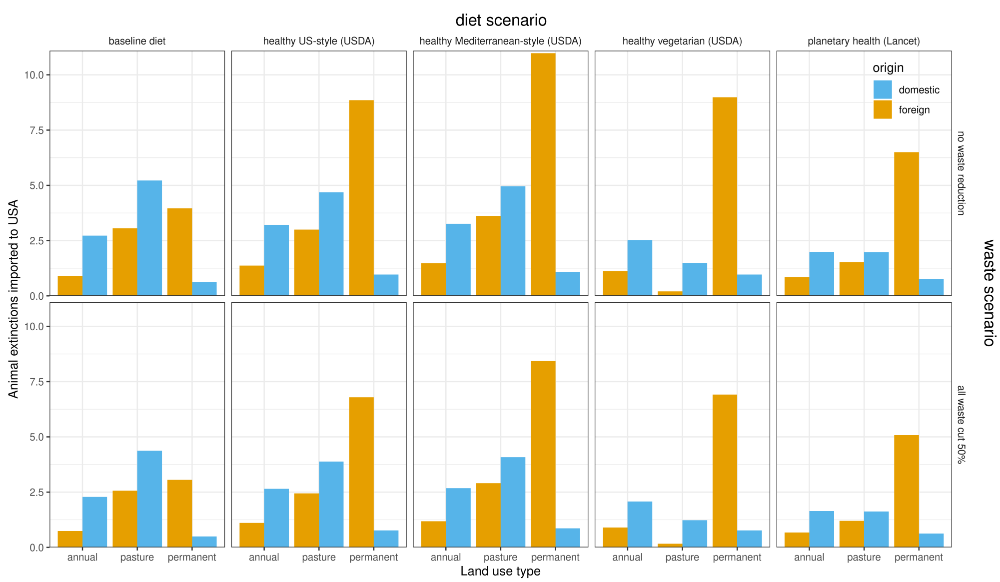

Figure S8: Total virtual biodiversity threat footprint in each scenario, by origin and land type: all animals summed

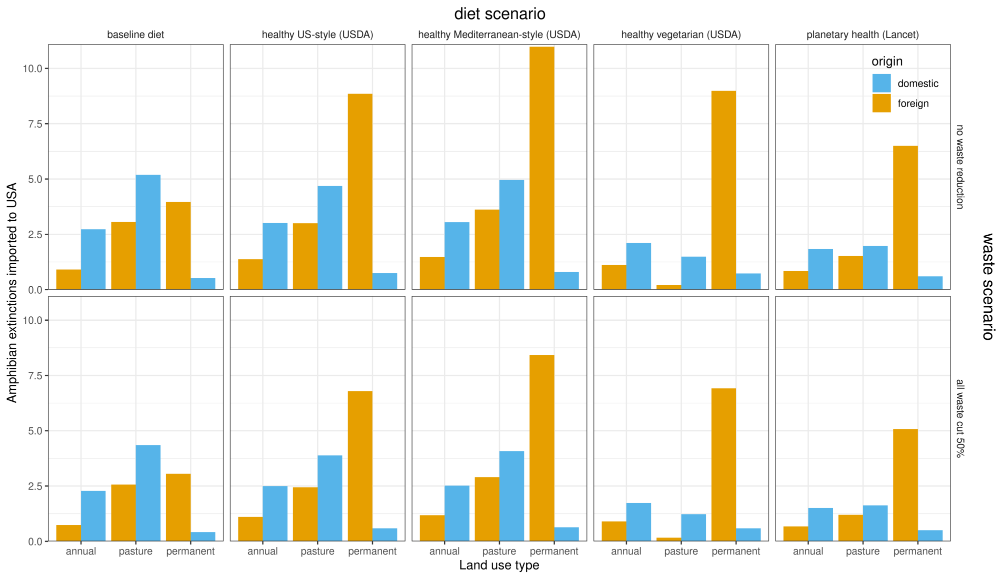

Figure S9: Total virtual biodiversity threat footprint in each scenario, by origin and land type: amphibians

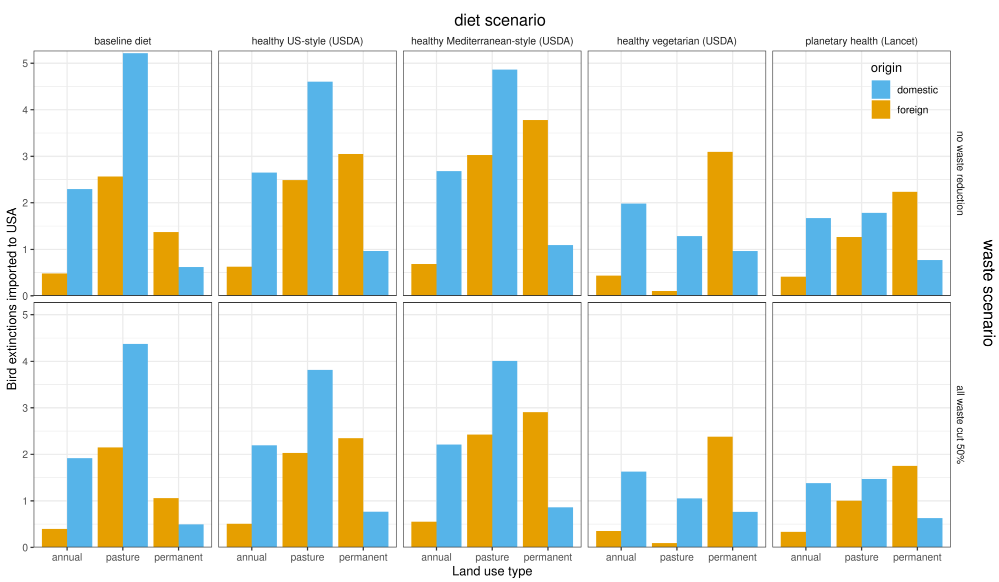

Figure S10: Total virtual biodiversity threat footprint in each scenario, by origin and land type: birds

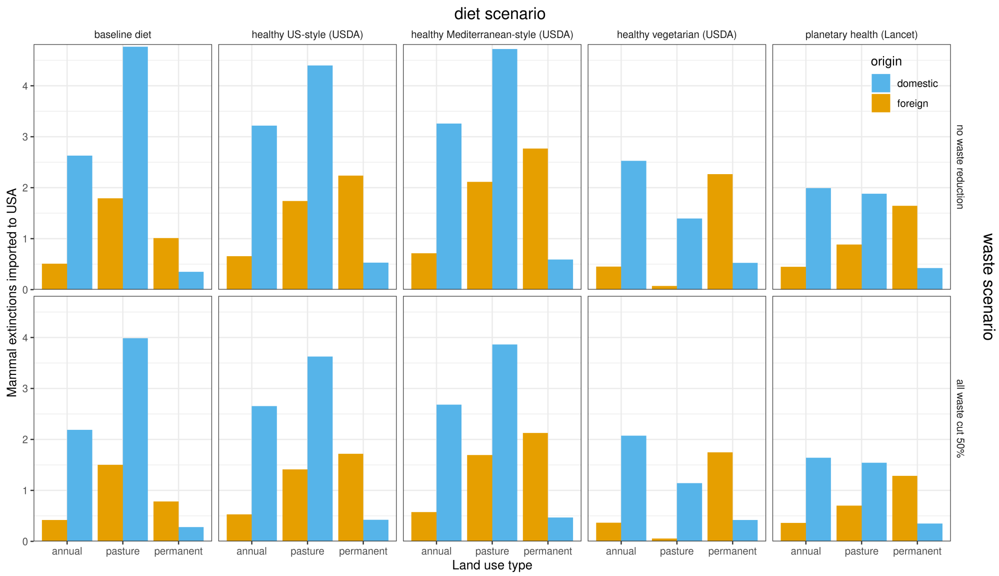

Figure S11: Total virtual biodiversity threat footprint in each scenario, by origin and land type: mammals

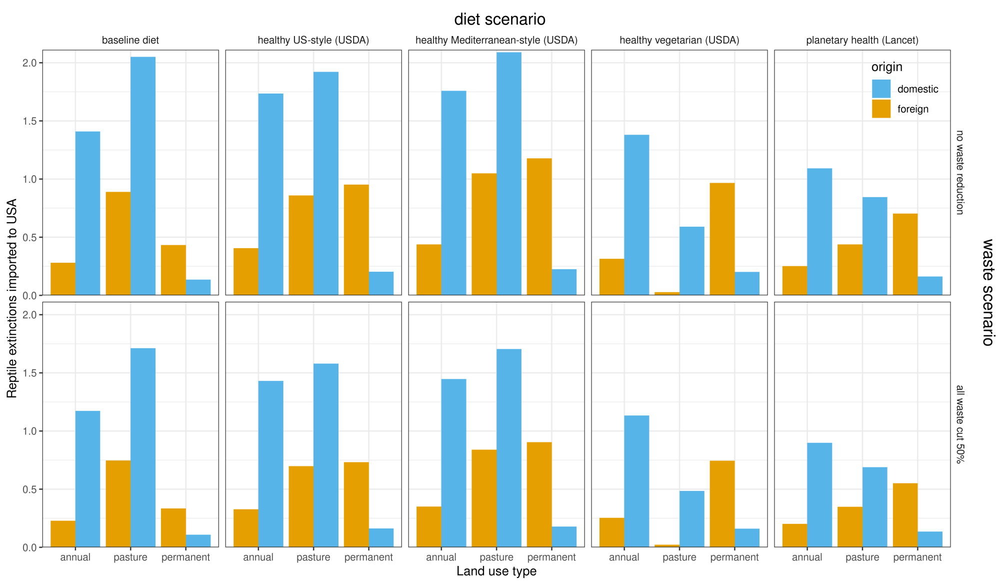

Figure S12: Total virtual biodiversity threat footprint in each scenario, by origin and land type: reptiles

Figures S13-S15. Maps showing domestic goods production

The following groups of figures in this document are maps showing values spatially disaggregated by county in the United States. In maps where we present absolute values of each of the quantities for each scenario, we use a colorblind-friendly `viridis` color gradient to fill the polygons on the maps. Note that the color gradient represents values on a logarithmic scale.

On the maps showing relative values, a colorblind-friendly `scico` divergent color gradient is used. Blue colors indicate decreases relative to the baseline and reddish-brown colors indicate increases. The starting or ending values of the color gradient are modified in each case so that white color indicates no change relative to baseline. On all maps, gray polygons indicate missing values or zero values that produce negative infinity when log-transformed.

The maps showing differences across scenarios have ten panels, each of which represents a combination of diet scenario (baseline, three USDA diets, and planetary health diet) and waste scenario (baseline and 50% reduction).

The contiguous United States map is displayed with an Albers equal-area projection for the continental United States identical to the one used by the National Land Cover Database. The inset maps for Alaska and Hawaii are displayed with Albers equal-area projections with parameters appropriate for those regions.

Figure S13 shows the absolute value of domestic production of all primary agricultural goods, in units of million USD (2012), with a log-transformed color gradient. Figure S14 shows the total across the ten groups of goods divided by the baseline value, resulting in a difference for each scenario relative to the baseline. Figure S15 shows the domestic production, by value in million USD, of the following ten primary agricultural goods listed above in this document, as well as the total, for the baseline scenario only. Each panel shows production for a different good.

- oilseeds and soybeans
- grains
- vegetables, including melons and potatoes
- fruits and nuts
- greenhouse crops grown for food, including mushrooms
- other crops, primarily sugar crops, peanuts, and herbs
- dairy products
- beef cattle
- poultry and eggs
- other meat, including farm-raised fish

Maps disaggregated by type of good across each scenario can be generated using the Shiny app.

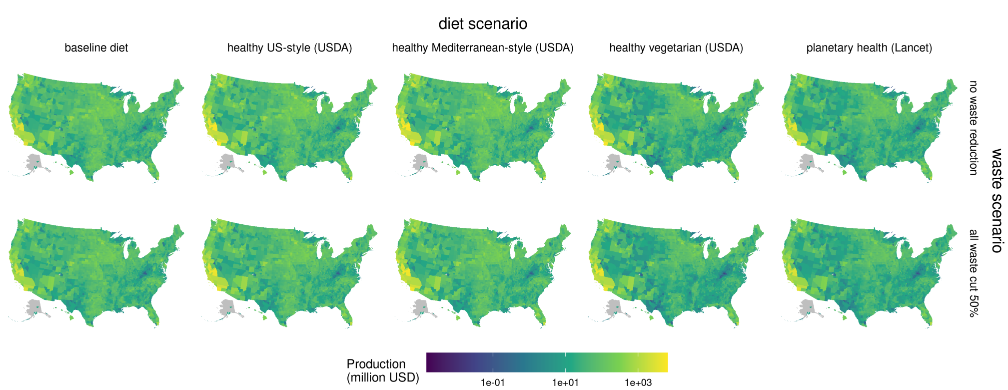

Figure S13: Total production value of all agricultural goods in each county by diet and waste scenario

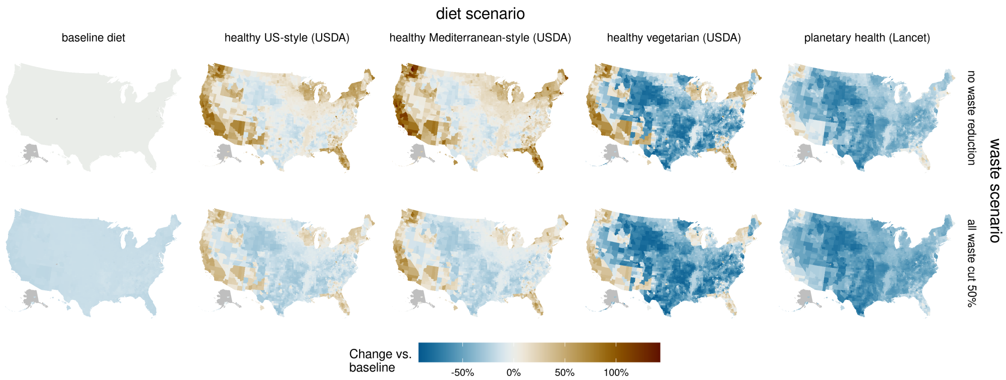

Figure S14: Change in production relative to baseline of all agricultural goods in each county by diet and waste scenario

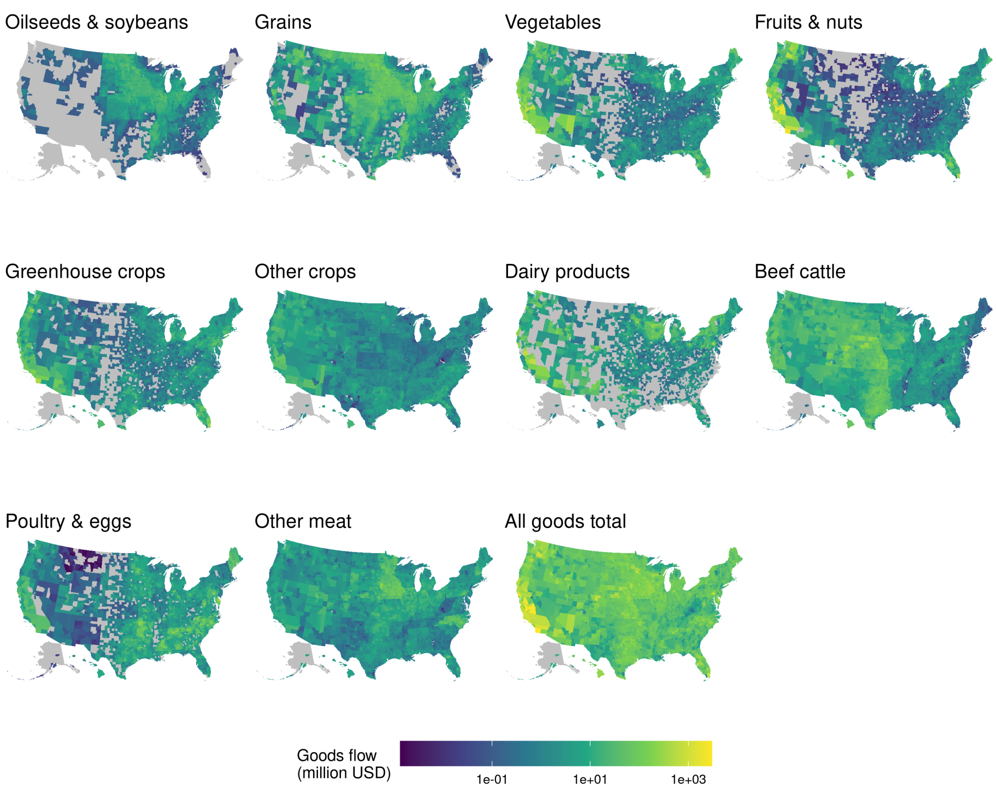

Figure S15: Total production value of agricultural goods in each county in the baseline scenario

Figures S16-S18. Maps showing land use in each county across scenarios

The following set of figures shows the land used in each county in the United States to produce food for domestic consumption under all combinations of diet and waste scenario, summed across all land use types (annual cropland, permanent cropland, and pastureland). Land use is shown in hectares (ha). Layout of panels and other details are the same as in the goods production figures above. Figure S16 shows the absolute values for each scenario, and Figure S17 the percent change relative to the baseline value. Maps disaggregated by land use type can be generated using the Shiny app.

Figure S18 shows land use for each of the land use types in the baseline scenario only. The figure has a separate panel for annual cropland, permanent cropland, pastureland, and the total across all four land use types.

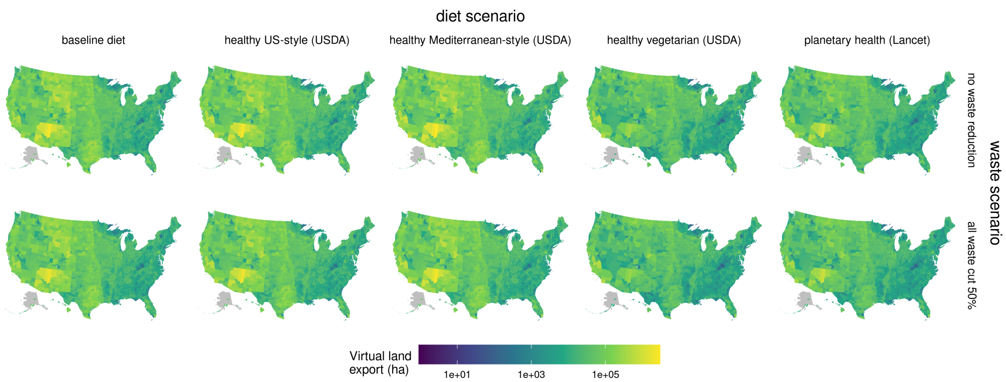

Figure S16: Land use summed across land use types in each county by diet and waste scenario

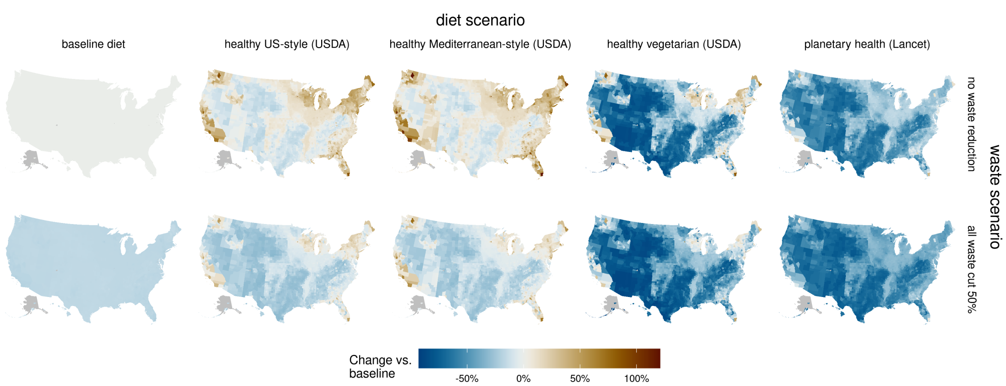

Figure S17: Change relative to baseline in land use summed across land use types in each county by diet and waste scenario

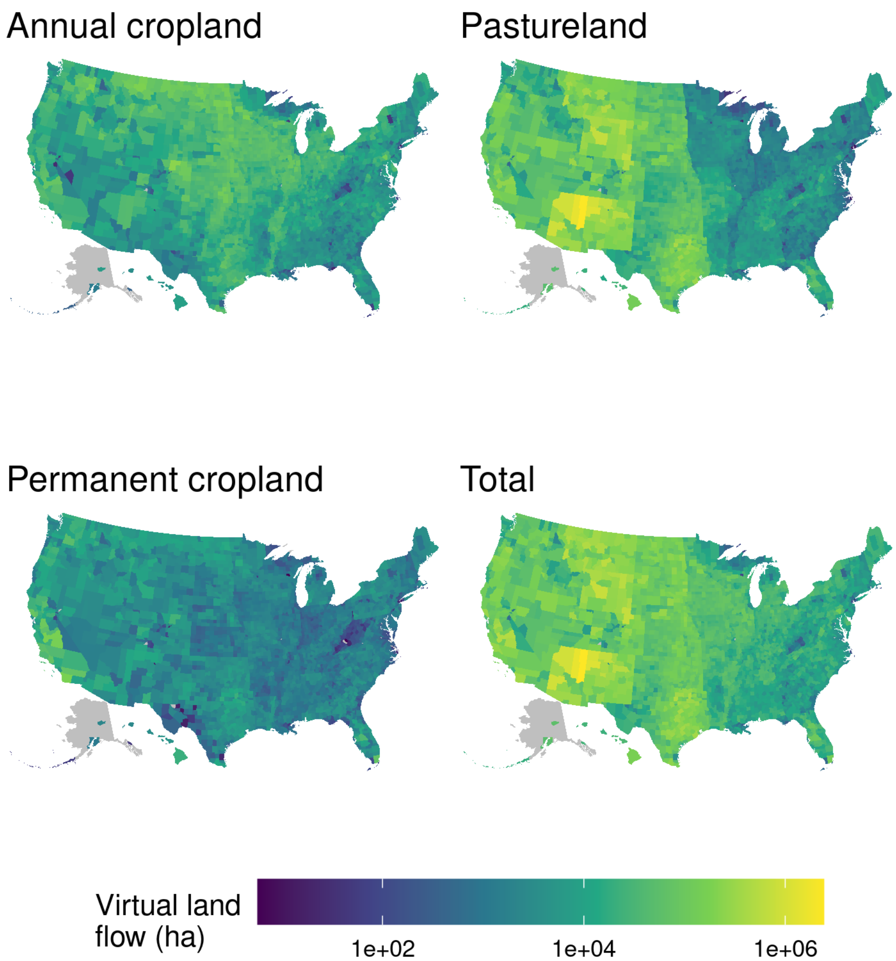

Figure S18:Land use by type in each county in the baseline scenario

Figures S19-S20. Maps showing foreign virtual land imports to the United States across scenarios

The following set of figures shows the virtual land imports to the United States from all foreign trading partners across all combinations of diet and waste scenarios, both as absolute values in hectares (Figure S19) and percentage change relative to baseline (Figure S20). These world maps use the Robinson equal-area projection. Color scales and layout of panels are as described above. Maps disaggregated by land use type can be generated using the Shiny app.

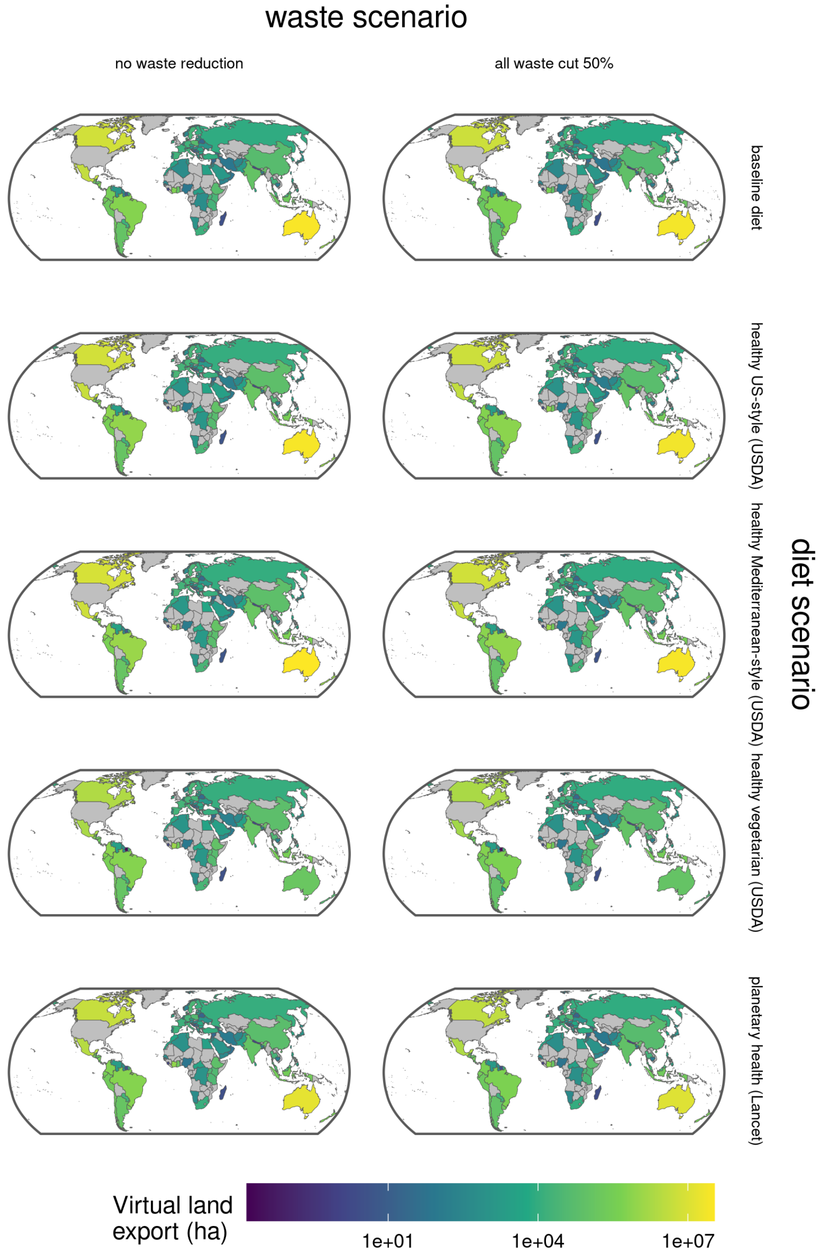

Figure S19: Virtual imports totaled across all land use types from all countries to the United States by diet and waste scenario

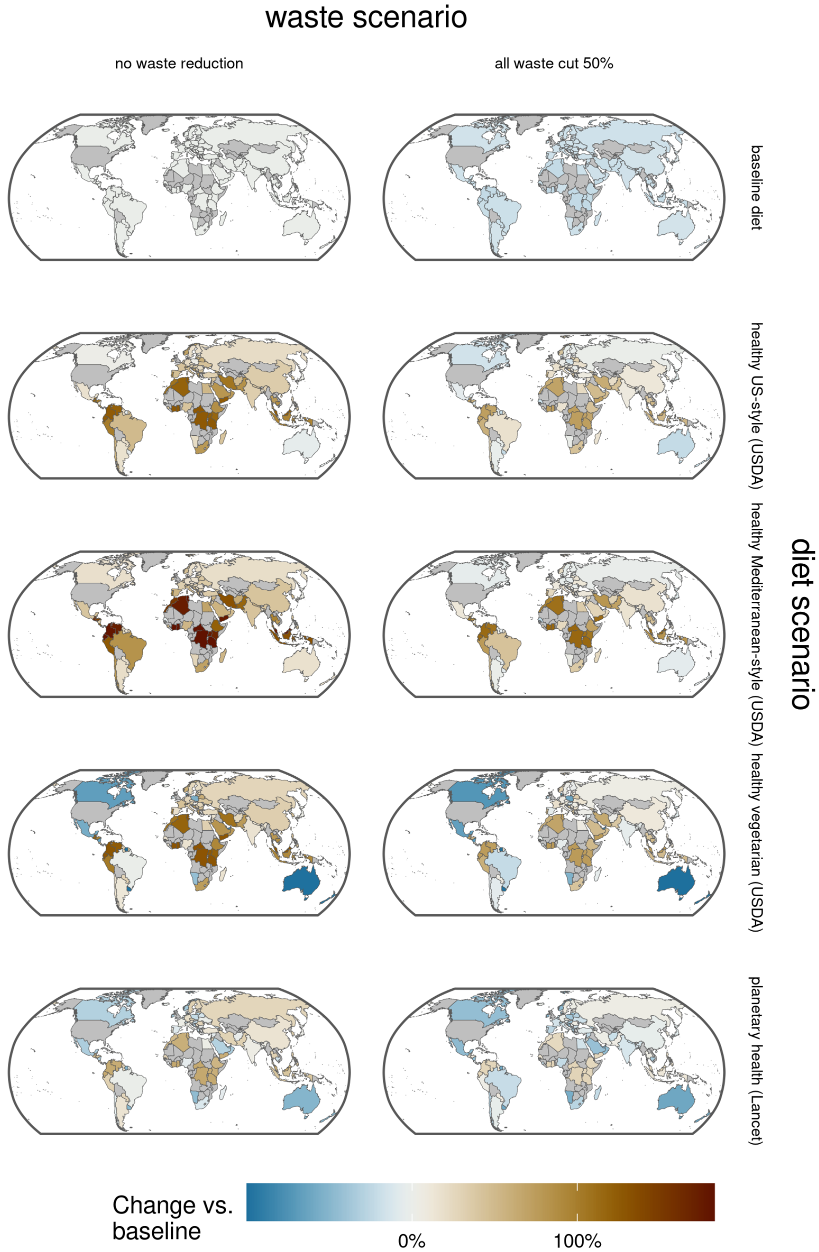

Figure S20: Change relative to baseline in virtual imports totaled across all land use types from all countries to the United States by diet and waste scenario

Figures S21-S26. Maps showing threatened biodiversity in each county across scenarios

The following set of figures shows the total biodiversity threat associated with food production in each county in the United States under all combinations of diet and waste scenario, with separate figures for plants, the sum of all animal taxa (amphibians, birds, mammals, and reptiles), and the total of plants and animals. Biodiversity threats are shown in units of number of species threatened by eventual global extinction. Layout of panels and other details are the same as in the goods production figures above. Figures S21-23 show the absolute values for each scenario for each of the taxonomic groups, and Figures S24-26 the percent change relative to the baseline value. Maps disaggregated by taxonomic group can be generated using the Shiny app.

Figure S27 shows the biodiversity threat for each of the taxonomic groups in the baseline scenario only. The figure has a separate panel for plants, amphibians, birds, mammals, reptiles, total across the four animal taxa, and total across both animals and plants.

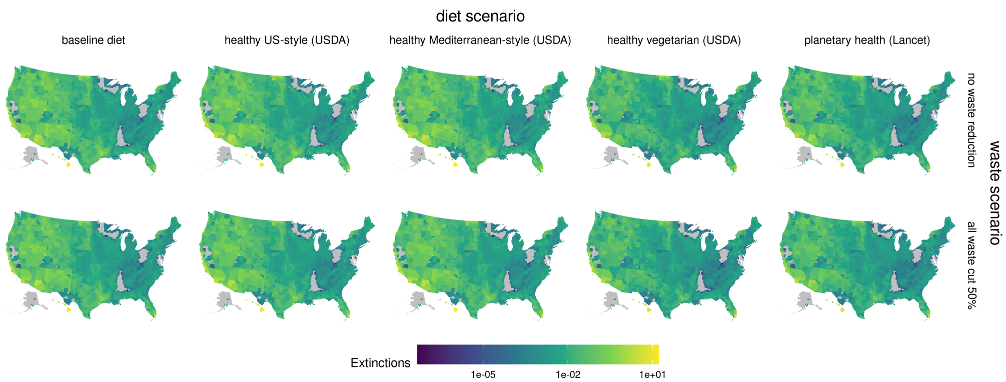

Figure S21: Threats to plant biodiversity in each county by diet and waste scenario

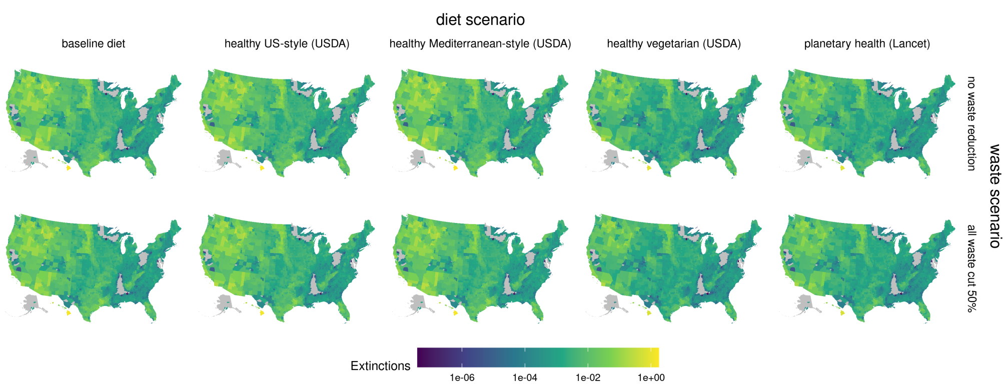

Figure S22: Threats to animal biodiversity in each county by diet and waste scenario (totaled across the four animal taxonomic groups)

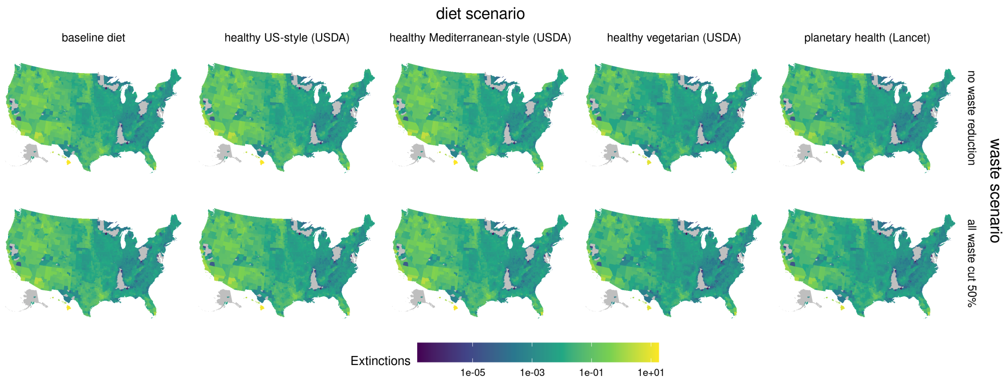

Figure S23: Threats to all biodiversity in each county by diet and waste scenario (totaled across all plant and animal taxa)

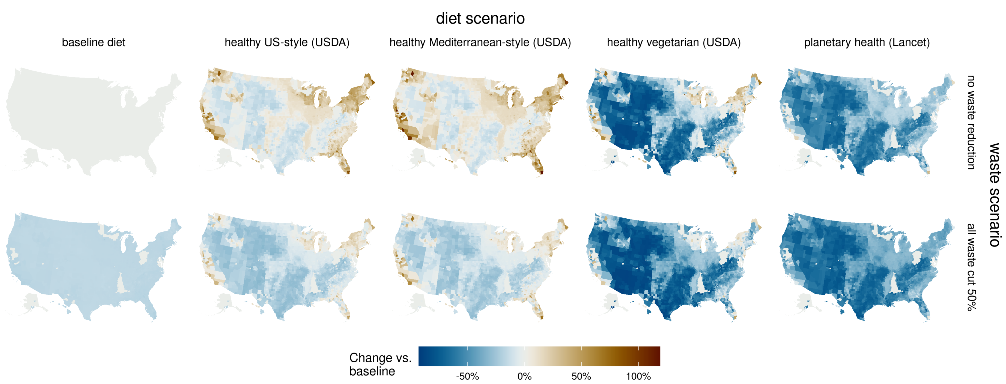

Figure S24: Change relative to baseline in threats to plant biodiversity in each county by diet and waste scenario

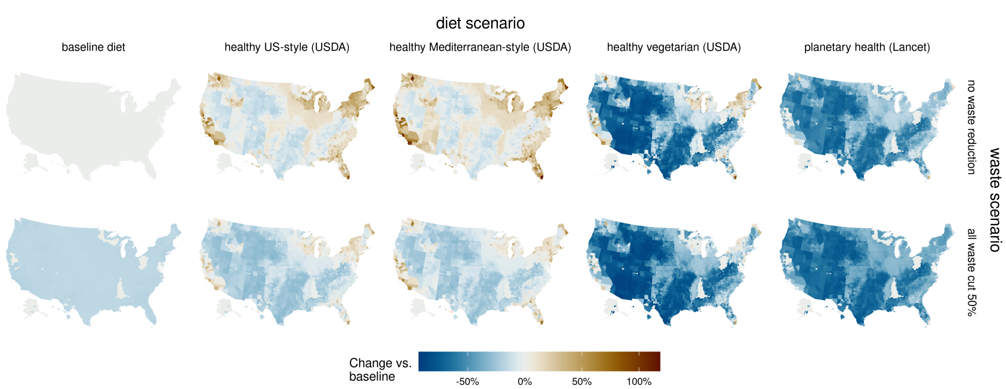

Figure S25: Change relative to baseline in threats to animal biodiversity in each county by diet and waste scenario (totaled across the four animal taxonomic groups)

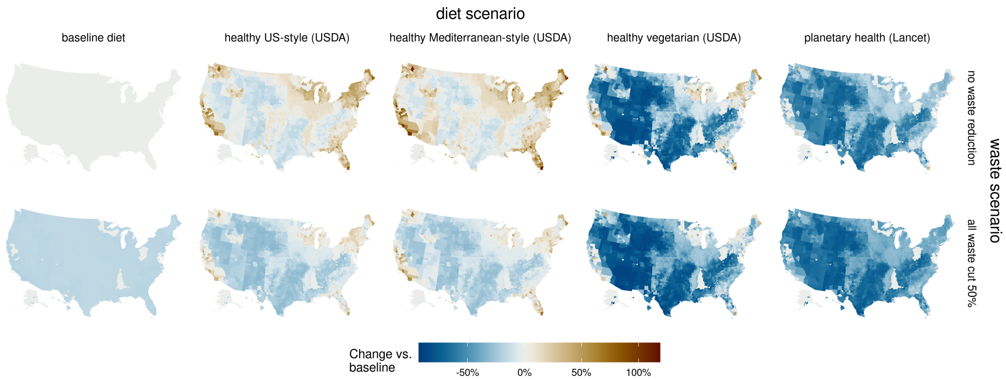

Figure S26: Change relative to baseline in threats to all biodiversity in each county by diet and waste scenario (totaled across all plant and animal taxa)

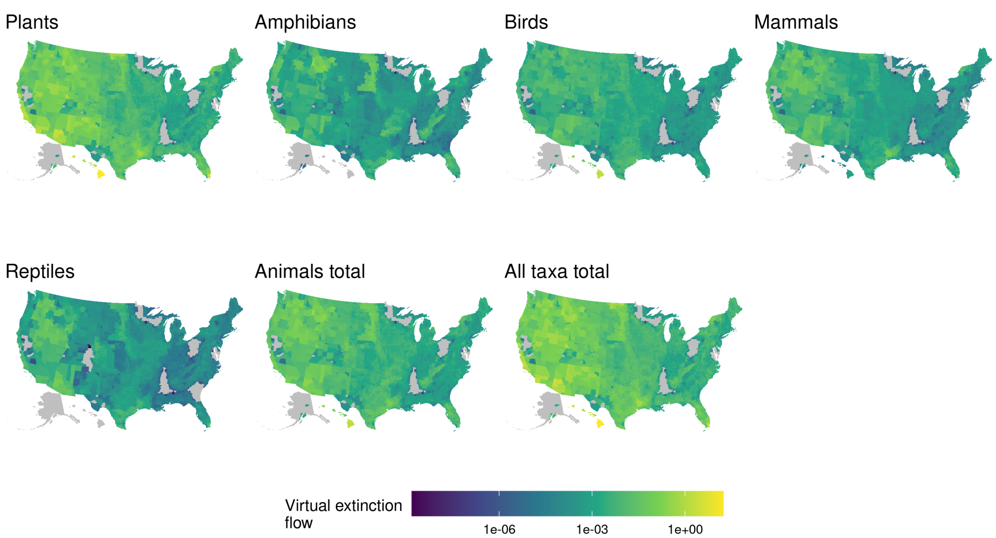

Figure S27: Biodiversity threats to each taxonomic group in each county in the baseline scenario

Figures S28-S33. Maps showing foreign virtual biodiversity threat imports to the United States across scenarios

The following set of figures shows the virtual biodiversity threat imports to the United States from all foreign trading partners across all combinations of diet and waste scenarios, both as absolute values in potential global species extinctions (Figures S28-S30) and percentage change relative to baseline (Figures S31-S33). A separate figure is shown for imported threats to plants, animals (total across taxa), and total of plant and animal threats. These world maps use the Robinson equal-area projection. Color scales and layout of panels are as described above.

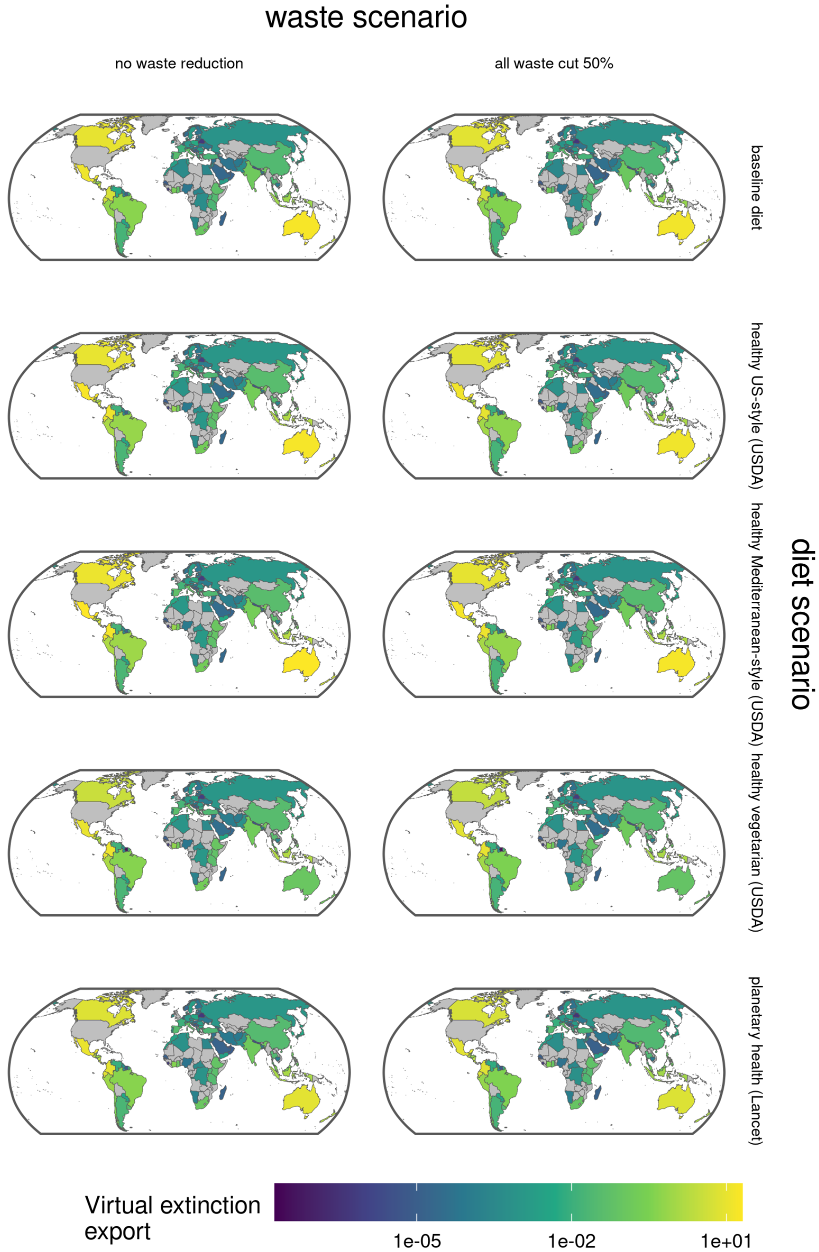

Figure S28: Virtual imports of threats to plant biodiversity from all countries to the United States by diet and waste scenario

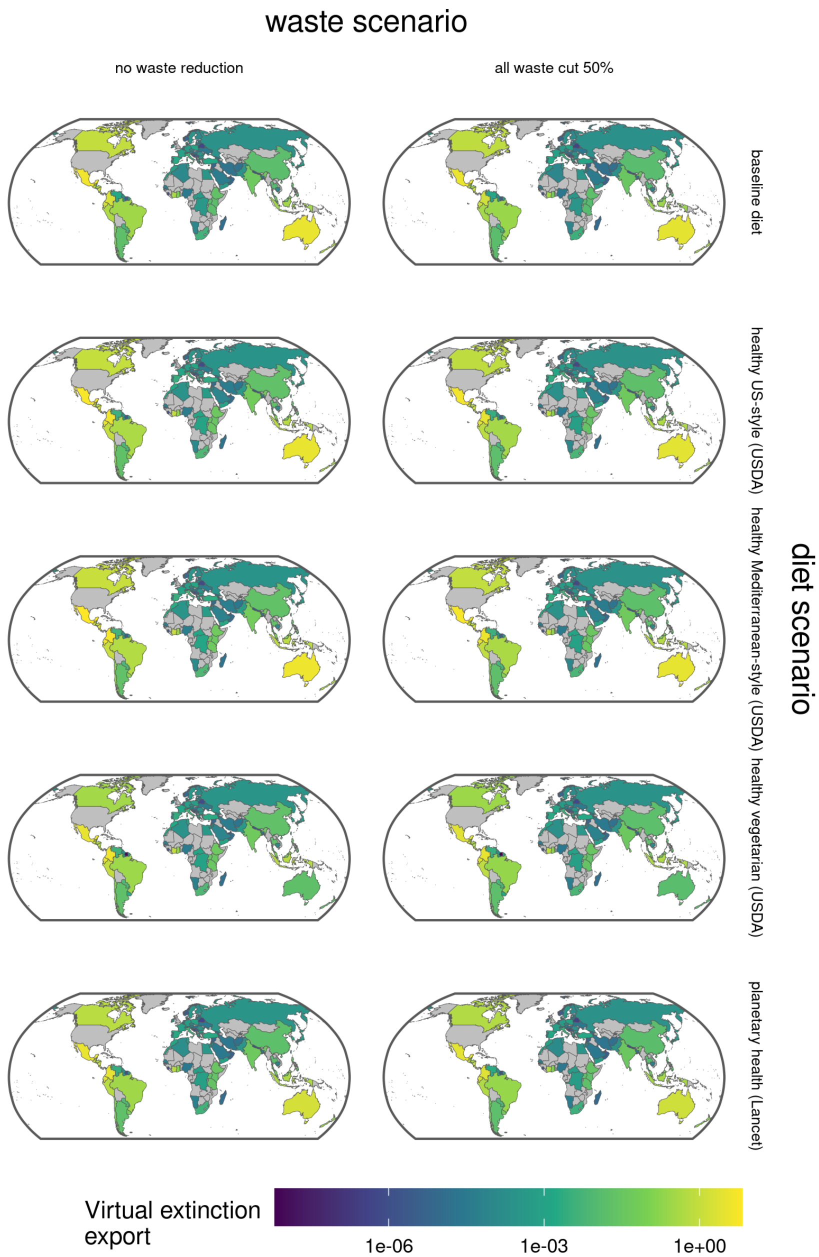

Figure S29: Virtual imports of threats to animal biodiversity from all countries to the United States by diet and waste scenario

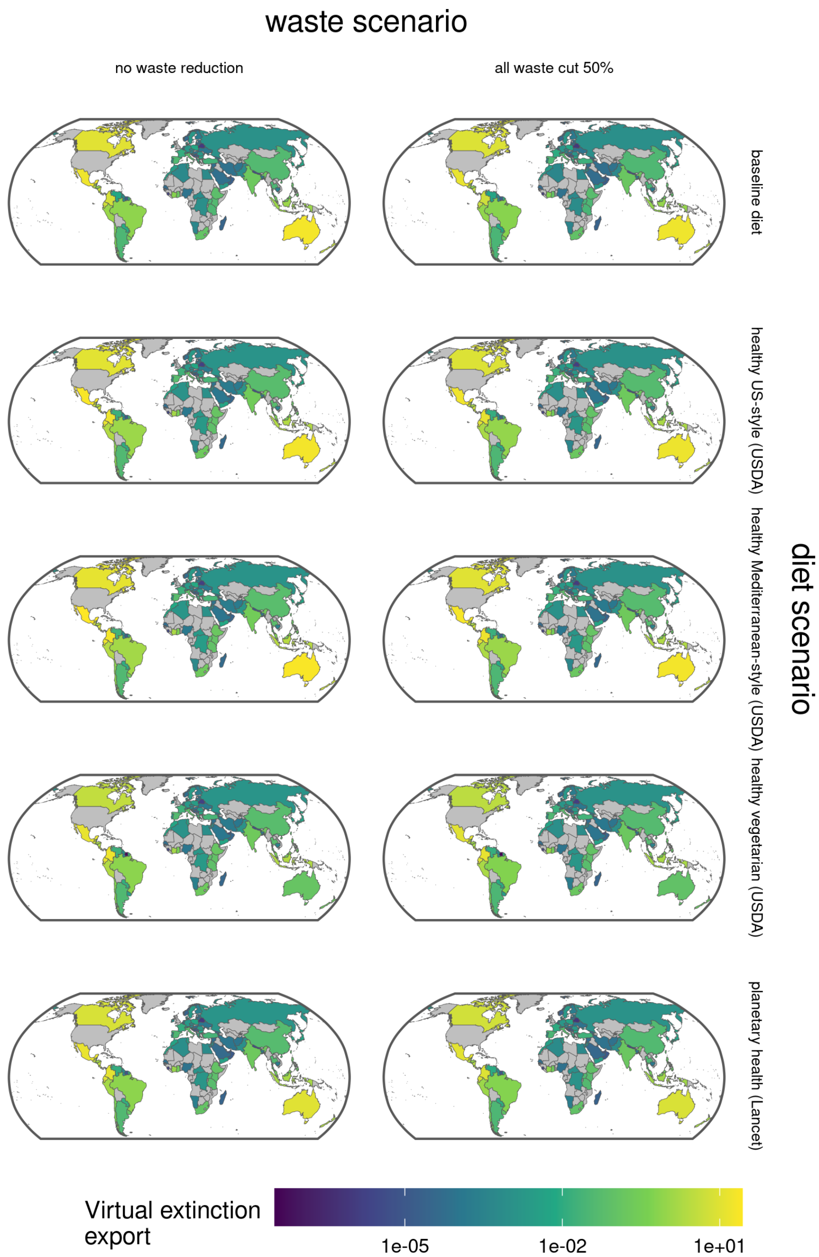

Figure S30: Virtual imports of total threats to plant and animal biodiversity from all countries to the United States by diet and waste scenario

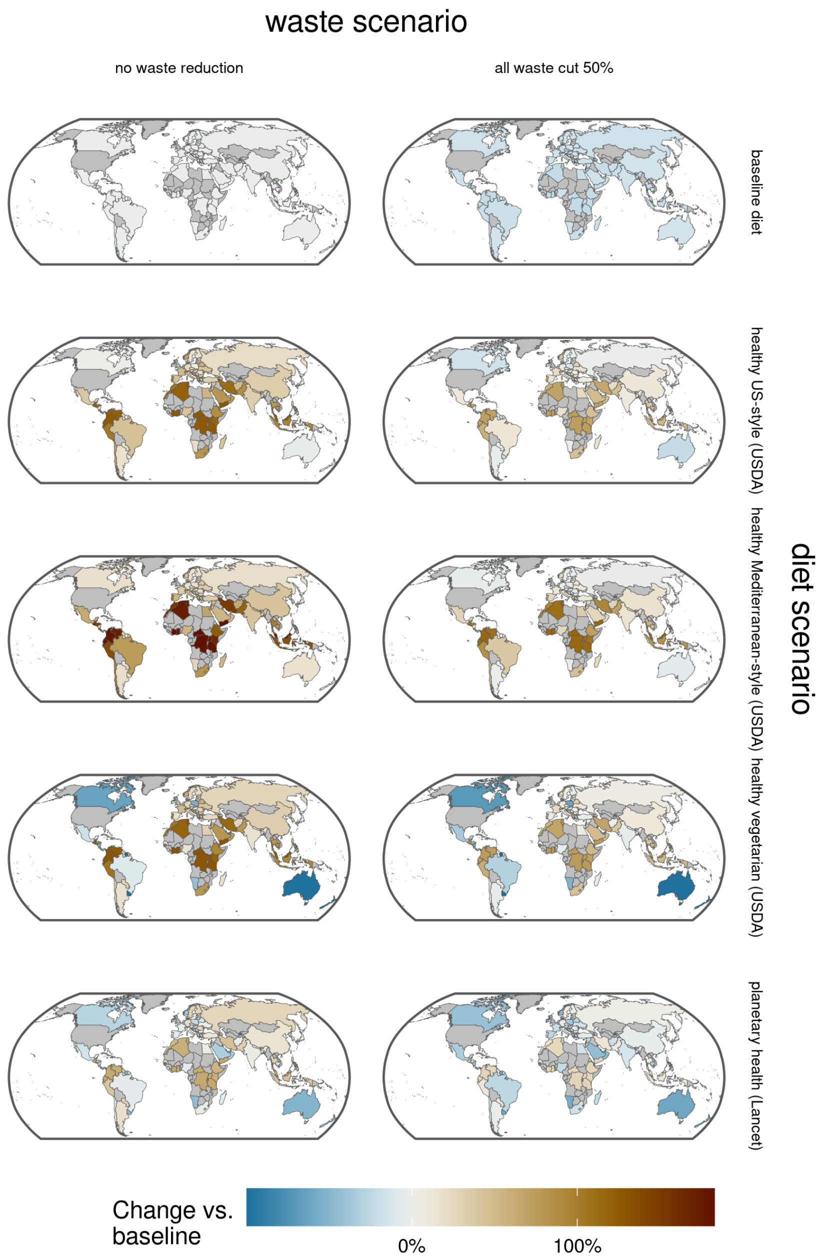

Figure S31: Change relative to baseline in virtual imports of threats to plant biodiversity from all countries to the United States by diet and waste scenario

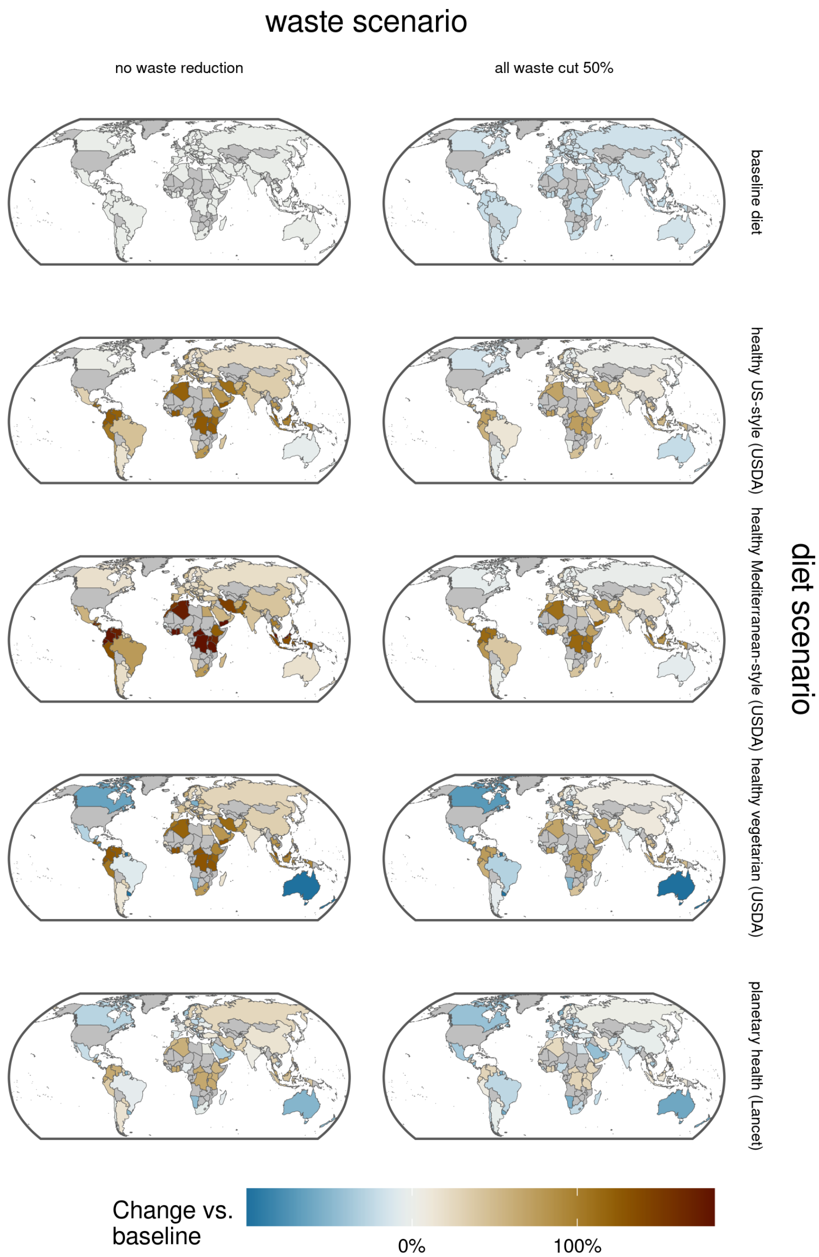

Figure S32: Change relative to baseline in virtual imports of threats to animal biodiversity from all countries to the United States by diet and waste scenario

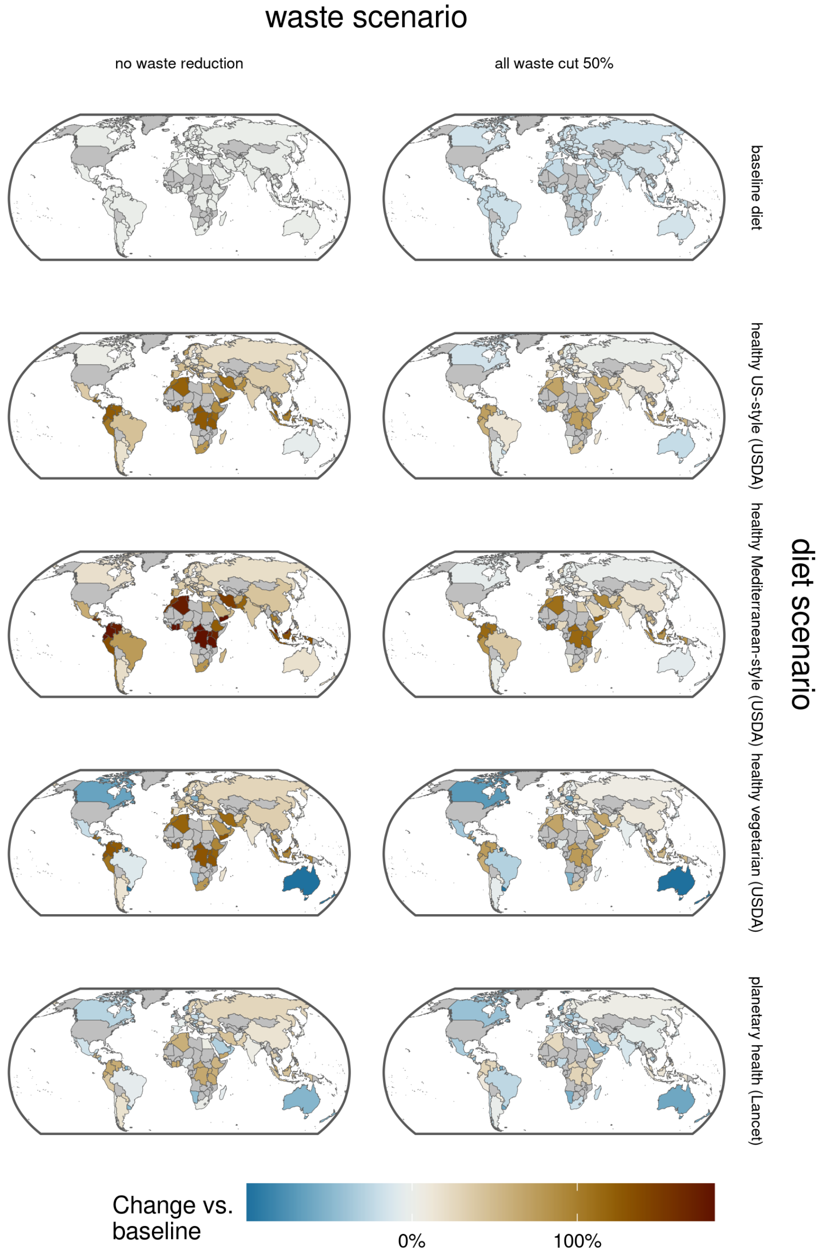

Figure S33: Change relative to baseline in virtual imports of total threats to plant and animal biodiversity from all countries to the United States by diet and waste scenario

Appendix 3: Supplemental tables

This appendix contains supplemental tables for the manuscript "Biodiversity effects of food system sustainability actions from farm to fork" by Quentin D. Read, Kelly L. Hondula, and Mary K. Muth.

Table S1. Total footprints and footprint intensities, baseline scenario

This table shows the total land and biodiversity threat footprint of food consumed in the United States in 2012 (baseline scenario). The land footprint is disaggregated by the three land use types (annual crops, permanent crops, and pasture) as well as origin (domestic and foreign), in units of 1000 km2. Biodiversity footprints associated with each of these six land footprint components are shown for animals, plants, and the total of the two, in units of potential global species extinctions. Footprints are rounded to the nearest whole number. The biodiversity footprints are divided by the land footprints to yield footprint intensities. Cell shading represents relative magnitude of values within each column.

	Total footprint				Footprint intensity		
	land 1000 km^2	animals extinctions	plants extinctions	total extinctions	animals extinctions/1000 km^2	plants extinctions/1000 km^2	total extinctions/1000 km^2
domestic origin							
annual cropland	643	9	22	31	0.014	0.034	0.048
permanent cropland	96	2	11	13	0.017	0.120	0.130
pastureland	1069	17	61	78	0.016	0.057	0.073
Total	*1807*	*28*	*94*	*122*	*0.016*	*0.059*	*0.073*
foreign origin							
annual cropland	55	2	12	14	0.040	0.220	0.260
permanent cropland	28	7	18	25	0.240	0.630	0.870
pastureland	367	8	31	40	0.023	0.085	0.110
Total	*451*	*17*	*61*	*78*	*0.110*	*0.270*	*0.380*
Grand Total	***2258***	***45***	***155***	***200***	***0.052***	***0.140***	***0.190***

Table S2. Total land used for domestic food consumption by U.S. state across scenarios

This table shows the total area of land consumed in each U.S. state to produce food consumed domestically in 2012, in units of square kilometers, summed across all agricultural land use types. For each of the 50 states, the value for the baseline scenario and the nine other counterfactual scenarios is provided (the baseline diet and four alternative diets crossed with baseline levels of food waste and 50% food waste reduction). After each value, the percentage change in each scenario relative to the baseline case is listed in parentheses.

	No waste reduction					50% waste reduction				
	baseline diet	USDA U.S. style	USDA Mediterranean	USDA vegetarian	Planetary Health	baseline diet	USDA U.S. style	USDA Mediterranean	USDA vegetarian	Planetary Health
Alabama	10800 (+0%)	10300 (-4.4%)	10600 (-1.6%)	5160 (-49.7%)	5510 (-47.7%)	9030 (-16.4%)	8520 (-20.9%)	8740 (-18.9%)	4220 (-58.9%)	4630 (-56.1%)
Alaska	2430 (+0%)	2480 (+2.2%)	2980 (+22.6%)	430 (-80.5%)	1170 (-51.6%)	2020 (-17.1%)	2000 (-17.6%)	2370 (-2.5%)	353 (-83.9%)	917 (-62.1%)
Arizona	76300 (+0%)	77000 (+1.1%)	92500 (+21.6%)	11200 (-84.6%)	34600 (-54.4%)	63200 (-17.1%)	62100 (-18.5%)	73600 (-3.3%)	9160 (-87.4%)	26900 (-64.5%)
Arkansas	21600 (+0%)	21200 (0%)	21500 (+1.2%)	12500 (-26.9%)	12600 (-33.3%)	18100 (-16.1%)	17700 (-16.8%)	17900 (-15.9%)	10400 (-39.5%)	10500 (-44.4%)
California	74200 (+0%)	99900 (+37.7%)	110000 (+52.5%)	77800 (+13.6%)	60500 (-13.9%)	60800 (-18.1%)	80400 (+10.4%)	87800 (+21.6%)	62100 (-9.6%)	49200 (-30.2%)
Colorado	69800 (+0%)	66500 (-4.2%)	68800 (-1%)	30600 (-48.6%)	33500 (-48.6%)	58400 (-16.2%)	55100 (-20.5%)	56900 (-18.2%)	25300 (-57.4%)	27900 (-57.2%)
Connecticut	586 (+0%)	742 (+26.9%)	764 (+30.7%)	551 (-5.2%)	437 (-25.2%)	485 (-17.3%)	606 (+3.6%)	621 (+6.1%)	447 (-23%)	358 (-38.8%)
Delaware	923 (+0%)	1120 (+20.9%)	1140 (+23.8%)	866 (-6%)	736 (-20.2%)	770 (-16.6%)	920 (-0.3%)	939 (+1.8%)	708 (-23.1%)	607 (-34.2%)
Florida	16900 (+0%)	21600 (+31.8%)	23800 (+46.7%)	15500 (+4.8%)	12100 (-21.2%)	13900 (-17.9%)	17400 (+5.8%)	19100 (+17.1%)	12300 (-17.2%)	9670 (-37.1%)
Georgia	10800 (+0%)	12300 (+14.9%)	12700 (+19.2%)	9050 (-9.4%)	8030 (-22.3%)	8920 (-17.4%)	10000 (-6.4%)	10300 (-3.2%)	7340 (-26.6%)	6760 (-34.6%)
Hawaii	2470 (+0%)	2420 (-1.8%)	2560 (+3.7%)	1120 (-52.7%)	1090 (-54.9%)	2070 (-16.6%)	1990 (-19.3%)	2090 (-15.1%)	904 (-62%)	891 (-63.3%)
Idaho	24500 (+0%)	28300 (+16.2%)	29200 (+19.6%)	19100 (-19.5%)	15700 (-35%)	20300 (-17.2%)	23200 (-4.9%)	23800 (-2.5%)	15600 (-34.4%)	13000 (-46.3%)
Illinois	41300 (+0%)	46700 (+13.2%)	47400 (+14.8%)	37000 (-10.2%)	33700 (-18.3%)	34400 (-16.6%)	38700 (-6.2%)	39200 (-5%)	30600 (-25.7%)	27900 (-32.2%)
Indiana	22100 (+0%)	24900 (+13%)	25400 (+15.4%)	19000 (-13.7%)	17500 (-20.6%)	18400 (-16.6%)	20600 (-6.4%)	21000 (-4.8%)	15700 (-28.6%)	14500 (-34.3%)
Iowa	51600 (+0%)	56900 (+10.3%)	58600 (+13.7%)	40300 (-21.4%)	38600 (-24.9%)	43100 (-16.5%)	47100 (-8.6%)	48400 (-6.2%)	33400 (-34.8%)	32000 (-37.8%)
Kansas	83300 (+0%)	86000 (+3.6%)	86900 (+4.7%)	55900 (-29.5%)	53100 (-34.2%)	70000 (-16%)	71700 (-13.6%)	72300 (-12.9%)	46500 (-41.5%)	44200 (-45.1%)
Kentucky	19100 (+0%)	18700 (-1.6%)	19000 (0%)	10400 (-42.4%)	10300 (-44%)	16000 (-16.5%)	15500 (-18.5%)	15700 (-17.4%)	8580 (-52.5%)	8650 (-53.1%)
Louisiana	11700 (+0%)	12000 (+2.5%)	12200 (+4.7%)	7460 (-30.6%)	7240 (-34.6%)	9780 (-16.6%)	9890 (-15.2%)	10100 (-13.6%)	6140 (-42.7%)	6050 (-45.2%)
Maine	2920 (+0%)	3710 (+29.7%)	3850 (+35.2%)	2710 (+0.4%)	2150 (-24.7%)	2440 (-16.5%)	3040 (+5.9%)	3140 (+9.9%)	2170 (-19.6%)	1760 (-38.5%)
Maryland	2970 (+0%)	3470 (+17.5%)	3490 (+17.9%)	2650 (-9.3%)	2230 (-24.3%)	2470 (-16.6%)	2870 (-2.9%)	2880 (-2.8%)	2180 (-25.2%)	1850 (-37.2%)
Massachusetts	697 (+0%)	973 (+40.3%)	1040 (+51.4%)	774 (+12.6%)	592 (-13.9%)	570 (-18.1%)	785 (+13.1%)	836 (+21.3%)	622 (-9.7%)	481 (-30.2%)
Michigan	15900 (+0%)	20100 (+26.8%)	20400 (+29.2%)	16500 (+4.8%)	13000 (-18%)	13200 (-17.1%)	16500 (+4.1%)	16700 (+5.6%)	13500 (-14.1%)	10700 (-32.4%)
Minnesota	41200 (+0%)	47900 (+16.4%)	48300 (+17.3%)	37500 (-8.3%)	32500 (-20.9%)	34400 (-16.6%)	39600 (-3.7%)	39900 (-3.2%)	31000 (-24.2%)	27000 (-34.3%)
Mississippi	12500 (+0%)	12900 (+3.5%)	13100 (+5.4%)	8340 (-28%)	8040 (-32.5%)	10400 (-16.7%)	10600 (-14.5%)	10800 (-13.1%)	6850 (-40.7%)	6710 (-43.6%)
Missouri	43200 (+0%)	42300 (-1.5%)	42900 (-0.2%)	24200 (-36.9%)	23800 (-40.2%)	36200 (-16.4%)	35200 (-18.2%)	35500 (-17.3%)	20000 (-47.9%)	19900 (-50.1%)
Montana	133000 (+0%)	124000 (-6.6%)	128000 (-3.2%)	51800 (-52.3%)	59900 (-51%)	112000 (-16.1%)	103000 (-22.4%)	106000 (-19.9%)	43000 (-60.4%)	49900 (-59.1%)
Nebraska	92100 (+0%)	88800 (-3.1%)	90100 (-1.7%)	48400 (-43.5%)	48800 (-44.4%)	77300 (-16.1%)	74000 (-19.3%)	74900 (-18.3%)	40100 (-53.2%)	40800 (-53.6%)
Nevada	13300 (+0%)	12000 (-9.8%)	12700 (-4.7%)	3750 (-70%)	5020 (-61.6%)	11100 (-16.4%)	9910 (-25.5%)	10400 (-21.8%)	3080 (-75.4%)	4160 (-68.1%)
New Hampshire	496 (+0%)	576 (+16.6%)	583 (+17.7%)	380 (-21.5%)	323 (-34.7%)	416 (-16.1%)	476 (-3.7%)	479 (-3.2%)	310 (-35.9%)	269 (-45.7%)
New Jersey	1310 (+0%)	1830 (+40.6%)	1940 (+49.4%)	1560 (+21%)	1190 (-8.5%)	1060 (-18.7%)	1470 (+13.2%)	1550 (+19.8%)	1260 (-2.7%)	960 (-26.2%)
New Mexico	105000 (+0%)	92200 (-11.7%)	98600 (-5.3%)	22400 (-77%)	35100 (-65.6%)	87700 (-16.2%)	76300 (-27%)	81000 (-22.3%)	18400 (-81.2%)	28700 (-71.9%)
New York	11200 (+0%)	16000 (+43.6%)	15700 (+40.5%)	14000 (+25.7%)	8650 (-22.2%)	9240 (-17.4%)	13200 (+17.8%)	12800 (+14.8%)	11500 (+3.2%)	7140 (-35.9%)
North Carolina	11400 (+0%)	12600 (+10.8%)	13000 (+14.8%)	8540 (-22.8%)	8050 (-28.2%)	9430 (-17.1%)	10300 (-9.2%)	10600 (-6.3%)	6980 (-37%)	6690 (-40.3%)
North Dakota	69000 (+0%)	73600 (+7.1%)	74900 (+8.9%)	51700 (-22.7%)	48800 (-27.9%)	57600 (-16.5%)	61100 (-11.2%)	62000 (-9.9%)	42700 (-36%)	40700 (-39.8%)
Ohio	20200 (+0%)	22900 (+13.8%)	23200 (+15%)	17200 (-12.9%)	15200 (-23.7%)	16800 (-16.8%)	18900 (-5.9%)	19100 (-5.2%)	14200 (-28%)	12600 (-36.7%)
Oklahoma	71200 (+0%)	66300 (-6.3%)	67800 (-4.2%)	30500 (-49.6%)	32300 (-50.4%)	59700 (-16.1%)	55200 (-22%)	56300 (-20.5%)	25200 (-58.3%)	27000 (-58.5%)
Oregon	35000 (+0%)	34900 (+0.5%)	36800 (+6.1%)	17100 (-46.5%)	17700 (-47.3%)	29200 (-16.7%)	28700 (-17.4%)	30200 (-13.2%)	13900 (-56.4%)	14600 (-56.6%)
Pennsylvania	11300 (+0%)	14400 (+28.6%)	14200 (+25.9%)	11500 (+4.2%)	8150 (-27.5%)	9370 (-17%)	11900 (+6%)	11600 (+3.5%)	9500 (-14.1%)	6780 (-39.7%)
Rhode Island	94.3 (+0%)	117 (+24.2%)	123 (+30.3%)	97.6 (+3.6%)	83.5 (-11.4%)	76.6 (-18.8%)	94.3 (+0%)	98.5 (+4.6%)	78.4 (-16.8%)	67.3 (-28.5%)
South Carolina	4920 (+0%)	5370 (+9.5%)	5570 (+13.6%)	3630 (-23.3%)	3440 (-28.5%)	4080 (-17%)	4400 (-10.2%)	4550 (-7.2%)	2960 (-37.3%)	2870 (-40.3%)
South Dakota	90600 (+0%)	86400 (-4.3%)	89800 (-0.5%)	40200 (-50.8%)	44900 (-48%)	75900 (-16.2%)	71700 (-20.6%)	74200 (-17.8%)	33300 (-59.2%)	37200 (-56.8%)
Tennessee	17400 (+0%)	16600 (-3.9%)	16900 (-2.3%)	8520 (-45.6%)	8550 (-47.2%)	14500 (-16.4%)	13800 (-20.2%)	14000 (-19.2%)	7020 (-55.2%)	7140 (-56%)
Texas	291000 (+0%)	264000 (-9.1%)	276000 (-4.8%)	93500 (-62.2%)	115000 (-57.7%)	244000 (-16.2%)	219000 (-24.7%)	228000 (-21.6%)	77000 (-68.8%)	95900 (-64.7%)
Utah	25800 (+0%)	25500 (-1%)	29300 (+13.6%)	6440 (-73%)	12100 (-52.8%)	21500 (-16.9%)	20800 (-19.5%)	23500 (-8.8%)	5310 (-77.8%)	9720 (-62.1%)
Vermont	1550 (+0%)	2160 (+39.7%)	2040 (+31.5%)	1800 (+18%)	1050 (-32.2%)	1290 (-16.7%)	1790 (+15.6%)	1680 (+8.6%)	1490 (-2.4%)	878 (-43.4%)
Virginia	12100 (+0%)	11800 (-1.8%)	12000 (-0.2%)	6030 (-45.4%)	5790 (-49.2%)	10100 (-16.4%)	9780 (-18.6%)	9900 (-17.6%)	4950 (-55.1%)	4830 (-57.7%)
Washington	23400 (+0%)	29500 (+27.3%)	30800 (+34.1%)	23600 (+3.7%)	18900 (-17.4%)	19400 (-17.3%)	24100 (+3.8%)	25100 (+8.8%)	19200 (-15.9%)	15600 (-31.9%)
West Virginia	4280 (+0%)	3840 (-10%)	3940 (-7.6%)	1390 (-65.7%)	1560 (-63%)	3590 (-16%)	3190 (-25.1%)	3260 (-23.5%)	1140 (-71.9%)	1290 (-69.3%)
Wisconsin	23200 (+0%)	31600 (+37%)	30300 (+31%)	27400 (+19%)	17200 (-25.6%)	19300 (-16.8%)	26200 (+13.3%)	25000 (+8.2%)	22600 (-1.7%)	14300 (-38.3%)
Wyoming	78400 (+0%)	68300 (-12.8%)	73200 (-6.5%)	15100 (-80.3%)	25700 (-66.8%)	65800 (-16.1%)	56500 (-27.9%)	60100 (-23.2%)	12500 (-83.7%)	21000 (-72.9%)

Table S3. Total biodiversity threatened by domestic food consumption by U.S. state across scenarios

This table shows the total biodiversity threat caused in each U.S. state by production of food consumed domestically in 2012, in units of potential global species extinctions, summed across all agricultural land use types and taxonomic groups threatened. For each of the 50 states, the value for the baseline scenario and the nine other counterfactual scenarios is provided (the baseline diet and four alternative diets crossed with baseline levels of food waste and 50% food waste reduction). After each value, the percentage change in each scenario relative to the baseline case is listed in parentheses.

	No waste reduction					50% waste reduction				
	baseline diet	USDA U.S. style	USDA Mediterranean	USDA vegetarian	Planetary Health	baseline diet	USDA U.S. style	USDA Mediterranean	USDA vegetarian	Planetary Health
Alabama	0.522 (+0%)	0.498 (-4.3%)	0.512 (-1.4%)	0.25 (-48.4%)	0.269 (-46.7%)	0.437 (-16.4%)	0.412 (-20.9%)	0.423 (-18.8%)	0.205 (-57.9%)	0.226 (-55.2%)
Alaska	0.0243 (+0%)	0.0245 (+0.6%)	0.0295 (+21.5%)	0.00323 (-85.5%)	0.0111 (-54.4%)	0.0202 (-17%)	0.0197 (-18.9%)	0.0235 (-3.4%)	0.00265 (-88.1%)	0.0086 (-64.5%)
Arizona	6.12 (+0%)	6.27 (+2.5%)	7.54 (+23.6%)	1.03 (-81%)	2.92 (-52%)	5.07 (-17.2%)	5.04 (-17.5%)	5.99 (-1.9%)	0.844 (-84.5%)	2.28 (-62.5%)
Arkansas	0.901 (+0%)	0.863 (-2.8%)	0.876 (-1.4%)	0.467 (-33.9%)	0.484 (-38.6%)	0.756 (-16%)	0.719 (-19.1%)	0.728 (-18.1%)	0.385 (-45.3%)	0.405 (-48.8%)
California	13.2 (+0%)	19 (+46.7%)	21.2 (+65.3%)	15.4 (+24.4%)	11.7 (-7.1%)	10.8 (-18.6%)	15.2 (+17%)	16.8 (+31.1%)	12.2 (-1.5%)	9.4 (-25.4%)
Colorado	2.16 (+0%)	2.01 (-6.8%)	2.09 (-2.9%)	0.786 (-55.1%)	0.918 (-54.1%)	1.81 (-16.2%)	1.66 (-22.7%)	1.73 (-19.9%)	0.648 (-62.8%)	0.761 (-61.8%)
Connecticut	0.0119 (+0%)	0.0151 (+27.3%)	0.0155 (+31.1%)	0.0113 (-3.7%)	0.00896 (-24.2%)	0.00981 (-17.3%)	0.0123 (+3.9%)	0.0126 (+6.4%)	0.0092 (-21.8%)	0.00734 (-37.9%)
Delaware	0.00284 (+0%)	0.00347 (+22.5%)	0.00356 (+25.5%)	0.00277 (-2.2%)	0.00232 (-18.1%)	0.00236 (-16.8%)	0.00286 (+0.9%)	0.00292 (+3%)	0.00227 (-19.9%)	0.00191 (-32.5%)
Florida	3.88 (+0%)	6.04 (+61.4%)	6.88 (+86.3%)	5.29 (+52.6%)	3.95 (+11.5%)	3.14 (-19.1%)	4.8 (+27.7%)	5.44 (+46.7%)	4.18 (+20.1%)	3.14 (-11.5%)
Georgia	0.432 (+0%)	0.5 (+16.9%)	0.516 (+21.1%)	0.389 (-3.9%)	0.342 (-17.7%)	0.356 (-17.6%)	0.407 (-5%)	0.419 (-1.8%)	0.316 (-22.1%)	0.289 (-30.5%)
Hawaii	22.6 (+0%)	23.4 (+5.5%)	24.9 (+12.4%)	12.8 (-30.6%)	11.7 (-41.7%)	18.8 (-16.8%)	19.2 (-13.9%)	20.3 (-8.6%)	10.3 (-44.5%)	9.52 (-52.7%)
Idaho	5.12 (+0%)	6 (+18.1%)	6.18 (+21.8%)	3.98 (-18.9%)	3.17 (-37%)	4.24 (-17.1%)	4.92 (-3.3%)	5.05 (-0.7%)	3.24 (-34%)	2.6 (-48.5%)
Illinois	0.52 (+0%)	0.589 (+13.3%)	0.598 (+15%)	0.468 (-9.9%)	0.425 (-18.1%)	0.434 (-16.6%)	0.488 (-6%)	0.494 (-4.9%)	0.387 (-25.5%)	0.353 (-32%)
Indiana	0.231 (+0%)	0.262 (+13.3%)	0.267 (+15.6%)	0.201 (-13.1%)	0.184 (-20.2%)	0.193 (-16.6%)	0.217 (-6.2%)	0.221 (-4.6%)	0.166 (-28.1%)	0.153 (-33.9%)
Iowa	0.653 (+0%)	0.72 (+10.3%)	0.741 (+13.5%)	0.51 (-21.4%)	0.487 (-25.1%)	0.545 (-16.5%)	0.596 (-8.6%)	0.611 (-6.3%)	0.423 (-34.8%)	0.403 (-38%)
Kansas	1.1 (+0%)	1.12 (+2.3%)	1.13 (+3.5%)	0.706 (-32.1%)	0.675 (-36.2%)	0.923 (-16%)	0.935 (-14.6%)	0.943 (-13.9%)	0.586 (-43.6%)	0.562 (-46.9%)
Kentucky	0.218 (+0%)	0.21 (-3.4%)	0.215 (-1.4%)	0.109 (-47.5%)	0.111 (-47.6%)	0.182 (-16.5%)	0.174 (-20.1%)	0.177 (-18.6%)	0.0894 (-56.8%)	0.0932 (-56.1%)
Louisiana	1.5 (+0%)	1.45 (-2.6%)	1.5 (+0.3%)	0.762 (-45.8%)	0.782 (-45.9%)	1.25 (-16.5%)	1.2 (-19.4%)	1.23 (-17.3%)	0.625 (-55.4%)	0.654 (-54.8%)
Maine	0.0896 (+0%)	0.116 (+32.2%)	0.121 (+38%)	0.0868 (+4.5%)	0.0676 (-22.8%)	0.0747 (-16.6%)	0.0952 (+7.8%)	0.0984 (+12%)	0.0697 (-16.3%)	0.0554 (-37%)
Maryland	0.0321 (+0%)	0.0394 (+23%)	0.0389 (+21.2%)	0.0305 (-3.5%)	0.0228 (-28.8%)	0.0267 (-16.8%)	0.0325 (+1.6%)	0.032 (-0.2%)	0.0252 (-20.3%)	0.0189 (-41%)
Massachusetts	0.0162 (+0%)	0.023 (+43.3%)	0.0249 (+56.3%)	0.0186 (+16.8%)	0.0142 (-10.6%)	0.0132 (-18.2%)	0.0185 (+15.2%)	0.0199 (+24.9%)	0.0149 (-6.5%)	0.0115 (-27.7%)
Michigan	0.281 (+0%)	0.358 (+28%)	0.363 (+30.6%)	0.296 (+6.8%)	0.231 (-17.2%)	0.233 (-17.2%)	0.294 (+4.9%)	0.297 (+6.6%)	0.243 (-12.6%)	0.191 (-31.7%)
Minnesota	0.436 (+0%)	0.511 (+17.6%)	0.514 (+18.2%)	0.405 (-6.6%)	0.345 (-20.6%)	0.363 (-16.6%)	0.423 (-2.7%)	0.425 (-2.4%)	0.335 (-22.7%)	0.287 (-34%)
Mississippi	0.311 (+0%)	0.315 (+1.8%)	0.323 (+4.1%)	0.188 (-32.2%)	0.183 (-36.6%)	0.26 (-16.5%)	0.261 (-15.8%)	0.266 (-14.1%)	0.154 (-44.1%)	0.152 (-47.4%)
Missouri	0.924 (+0%)	0.892 (-2.8%)	0.904 (-1.5%)	0.484 (-40.1%)	0.482 (-42.9%)	0.773 (-16.3%)	0.741 (-19.3%)	0.749 (-18.4%)	0.399 (-50.6%)	0.402 (-52.4%)
Montana	8.3 (+0%)	7.5 (-9.3%)	7.9 (-4.5%)	2.5 (-65.4%)	3.28 (-58.5%)	6.95 (-16.2%)	6.21 (-24.9%)	6.51 (-21.3%)	2.06 (-71.4%)	2.72 (-65.6%)
Nebraska	1.58 (+0%)	1.48 (-5.3%)	1.5 (-4%)	0.754 (-46.9%)	0.773 (-47.5%)	1.32 (-16.1%)	1.24 (-21%)	1.25 (-20.2%)	0.625 (-56%)	0.647 (-56.1%)
Nevada	3.12 (+0%)	2.81 (-9.8%)	2.96 (-4.8%)	0.89 (-69.5%)	1.18 (-61.4%)	2.61 (-16.4%)	2.32 (-25.5%)	2.43 (-21.9%)	0.732 (-74.9%)	0.977 (-67.9%)
New Hampshire	0.0108 (+0%)	0.0126 (+17.1%)	0.0127 (+18.2%)	0.00843 (-19.9%)	0.00712 (-33.7%)	0.00902 (-16.2%)	0.0104 (-3.3%)	0.0104 (-2.8%)	0.00687 (-34.6%)	0.00592 (-44.9%)
New Jersey	0.0359 (+0%)	0.0506 (+41.9%)	0.0537 (+50.9%)	0.0438 (+23.5%)	0.0332 (-7%)	0.0292 (-18.7%)	0.0408 (+14.2%)	0.0431 (+20.9%)	0.0352 (-0.8%)	0.0268 (-25.1%)
New Mexico	5.03 (+0%)	4.38 (-12.7%)	4.65 (-7.1%)	1.05 (-77.6%)	1.62 (-66.9%)	4.21 (-16.1%)	3.63 (-27.7%)	3.83 (-23.6%)	0.863 (-81.5%)	1.33 (-72.9%)
New York	0.658 (+0%)	0.954 (+45.3%)	0.911 (+38.8%)	0.845 (+29.3%)	0.493 (-24.8%)	0.544 (-17.3%)	0.785 (+19.6%)	0.748 (+13.9%)	0.696 (+6.5%)	0.409 (-37.6%)
North Carolina	0.304 (+0%)	0.338 (+11.5%)	0.349 (+15.4%)	0.238 (-19.9%)	0.225 (-25.1%)	0.252 (-17.1%)	0.277 (-8.6%)	0.285 (-5.7%)	0.194 (-34.5%)	0.187 (-37.6%)
North Dakota	6.66 (+0%)	7.28 (+9.5%)	7.39 (+11%)	5.46 (-17.1%)	5.07 (-23.2%)	5.56 (-16.5%)	6.04 (-9.2%)	6.11 (-8.1%)	4.52 (-31.4%)	4.23 (-35.9%)
Ohio	0.187 (+0%)	0.211 (+12.5%)	0.214 (+14.2%)	0.165 (-11.2%)	0.151 (-19.3%)	0.156 (-16.7%)	0.174 (-6.9%)	0.176 (-5.7%)	0.137 (-26.6%)	0.125 (-33%)
Oklahoma	1.2 (+0%)	1.09 (-9%)	1.11 (-6.9%)	0.445 (-55.8%)	0.491 (-55.2%)	1.01 (-16.1%)	0.906 (-24.2%)	0.925 (-22.7%)	0.367 (-63.4%)	0.411 (-62.6%)
Oregon	4.45 (+0%)	4.34 (-1.9%)	4.53 (+2.4%)	2.03 (-48%)	2.12 (-49.1%)	3.72 (-16.4%)	3.59 (-18.9%)	3.73 (-15.8%)	1.66 (-57.2%)	1.75 (-57.9%)
Pennsylvania	0.278 (+0%)	0.361 (+30.3%)	0.352 (+26.9%)	0.295 (+7.4%)	0.204 (-26.5%)	0.231 (-17%)	0.297 (+7.4%)	0.289 (+4.3%)	0.243 (-11.4%)	0.17 (-38.8%)
Rhode Island	0.00229 (+0%)	0.00286 (+24.8%)	0.003 (+30.9%)	0.0024 (+4.8%)	0.00204 (-10.9%)	0.00186 (-18.8%)	0.00231 (+0.5%)	0.00241 (+5%)	0.00193 (-15.8%)	0.00165 (-28.1%)
South Carolina	0.144 (+0%)	0.16 (+11.4%)	0.166 (+15.2%)	0.115 (-18%)	0.107 (-24.4%)	0.12 (-17.1%)	0.132 (-8.7%)	0.136 (-5.9%)	0.094 (-32.9%)	0.0898 (-36.8%)
South Dakota	3.15 (+0%)	3.02 (-3.8%)	3.12 (-0.5%)	1.49 (-49.6%)	1.62 (-47%)	2.64 (-16.2%)	2.51 (-20.1%)	2.58 (-17.8%)	1.24 (-58.3%)	1.34 (-56%)
Tennessee	0.471 (+0%)	0.435 (-7.4%)	0.441 (-6.1%)	0.19 (-57.9%)	0.194 (-57.7%)	0.394 (-16.2%)	0.362 (-23.1%)	0.366 (-22.2%)	0.156 (-65.4%)	0.162 (-64.7%)
Texas	14.9 (+0%)	13.7 (-7.9%)	14.3 (-3.5%)	5.12 (-58.7%)	6.16 (-55.4%)	12.5 (-16.3%)	11.3 (-23.8%)	11.8 (-20.6%)	4.21 (-66%)	5.12 (-62.7%)
Utah	3.8 (+0%)	3.8 (+0.1%)	4.37 (+15%)	0.993 (-71.3%)	1.84 (-51.5%)	3.16 (-16.9%)	3.09 (-18.7%)	3.51 (-7.7%)	0.817 (-76.4%)	1.47 (-61%)
Vermont	0.174 (+0%)	0.251 (+45.2%)	0.234 (+35.1%)	0.218 (+26.9%)	0.12 (-31.1%)	0.144 (-16.8%)	0.208 (+20.1%)	0.194 (+11.6%)	0.181 (+5.1%)	0.0999 (-42.5%)
Virginia	0.355 (+0%)	0.34 (-3.6%)	0.344 (-2.4%)	0.166 (-48.5%)	0.161 (-51.9%)	0.297 (-16.3%)	0.282 (-20.1%)	0.285 (-19.3%)	0.137 (-57.7%)	0.135 (-59.9%)
Washington	3.71 (+0%)	4.5 (+22%)	4.62 (+25.5%)	3.56 (-2.3%)	2.94 (-19.5%)	3.09 (-16.7%)	3.71 (+0.4%)	3.8 (+3%)	2.92 (-19.9%)	2.43 (-33.4%)
West Virginia	0.077 (+0%)	0.0696 (-9.3%)	0.0715 (-6.7%)	0.0255 (-64.7%)	0.0284 (-62.3%)	0.0647 (-16%)	0.0579 (-24.6%)	0.0593 (-22.7%)	0.0209 (-71.1%)	0.0236 (-68.7%)
Wisconsin	0.301 (+0%)	0.408 (+35.8%)	0.393 (+30.7%)	0.352 (+17.5%)	0.227 (-24.5%)	0.251 (-16.9%)	0.338 (+12.2%)	0.324 (+7.8%)	0.291 (-3%)	0.188 (-37.5%)
Wyoming	1.81 (+0%)	1.59 (-11.9%)	1.71 (-5%)	0.358 (-79.3%)	0.611 (-65.6%)	1.51 (-16.2%)	1.31 (-27.2%)	1.4 (-22.1%)	0.296 (-82.9%)	0.499 (-71.9%)

Table S4. Virtual land imported to the United States by foreign country across scenarios

This table shows the total area of land consumed in each of the United States' trading partners to produce food consumed in the United States in 2012, in units of square kilometers, summed across all agricultural land use types. Only the top 20 trading partners, sorted in descending order by the size of the biodiversity threat they virtually exported to the United States in 2012 (baseline scenario) are listed. The remaining countries are aggregated into the category "Other," which accounts for less than 8% of the United States' virtual land imports. For each of the 20 countries, the value for the baseline scenario and the nine other counterfactual scenarios is provided (the baseline diet and four alternative diets crossed with baseline levels of food waste and 50% food waste reduction). After each value, the percentage change in each scenario relative to the baseline case is listed in parentheses.

	No waste reduction					50% waste reduction				
	baseline diet	USDA U.S. style	USDA Mediterranean	USDA vegetarian	Planetary Health	baseline diet	USDA U.S. style	USDA Mediterranean	USDA vegetarian	Planetary Health
Australia (AUS)	285000 (+0%)	272000 (-4.7%)	335000 (+17.5%)	1440 (-99.5%)	140000 (-50.9%)	239000 (-16.1%)	221000 (-22.5%)	268000 (-6%)	1040 (-99.6%)	111000 (-61.1%)
Mexico (MEX)	42200 (+0%)	49500 (+17.4%)	59400 (+40.9%)	17800 (-57.7%)	28100 (-33.4%)	34900 (-17.2%)	39700 (-5.8%)	47100 (+11.8%)	14000 (-66.9%)	22200 (-47.4%)
Canada (CAN)	69300 (+0%)	70700 (+2%)	82100 (+18.6%)	22500 (-67.5%)	47900 (-30.8%)	57800 (-16.5%)	57600 (-16.8%)	66100 (-4.6%)	18400 (-73.4%)	38600 (-44.2%)
Colombia (COL)	3300 (+0%)	7430 (+125.3%)	9230 (+179.8%)	7530 (+128.4%)	5420 (+64.3%)	2540 (-22.8%)	5700 (+72.9%)	7080 (+114.6%)	5790 (+75.6%)	4220 (+28.1%)
Ecuador (ECU)	2250 (+0%)	5090 (+125.9%)	6320 (+180.6%)	5170 (+129.5%)	3710 (+64.7%)	1740 (-22.9%)	3910 (+73.4%)	4850 (+115.2%)	3980 (+76.5%)	2890 (+28.4%)
Nicaragua (NIC)	5590 (+0%)	6370 (+13.9%)	7740 (+38.5%)	2020 (-63.9%)	3700 (-33.9%)	4640 (-17%)	5110 (-8.6%)	6140 (+9.7%)	1570 (-71.9%)	2930 (-47.7%)
New Zealand (NZL)	8760 (+0%)	8520 (-2.8%)	10400 (+18.4%)	388 (-95.6%)	4350 (-50.3%)	7350 (-16.1%)	6930 (-20.9%)	8310 (-5.2%)	314 (-96.4%)	3460 (-60.6%)
Costa Rica (CRI)	1140 (+0%)	2050 (+79.5%)	2500 (+119%)	1720 (+51%)	1390 (+21.9%)	906 (-20.5%)	1590 (+39.6%)	1930 (+69.7%)	1330 (+16.6%)	1090 (-4.5%)
Guatemala (GTM)	1760 (+0%)	3840 (+117.7%)	4620 (+162.1%)	3890 (+120.6%)	2680 (+52.1%)	1370 (-22.5%)	2970 (+68.2%)	3560 (+102.1%)	3010 (+70.8%)	2100 (+18.9%)
Indonesia (IDN)	1950 (+0%)	3810 (+95.6%)	4550 (+133.5%)	3730 (+91.6%)	2750 (+41.4%)	1540 (-21%)	2970 (+52.5%)	3530 (+81.5%)	2910 (+49.5%)	2180 (+12.2%)
Peru (PER)	1730 (+0%)	3480 (+101%)	3910 (+125.9%)	3510 (+103.2%)	2270 (+31.4%)	1370 (-20.6%)	2740 (+58.3%)	3060 (+76.9%)	2770 (+60.2%)	1800 (+4%)
Brazil (BRA)	6110 (+0%)	9170 (+49.9%)	11200 (+83.8%)	6140 (+0.5%)	6110 (-0.1%)	4960 (-18.9%)	7200 (+17.8%)	8770 (+43.4%)	4750 (-22.4%)	4800 (-21.4%)
Honduras (HND)	929 (+0%)	1890 (+103%)	2300 (+147.1%)	1800 (+94.2%)	1330 (+43.4%)	727 (-21.7%)	1460 (+57%)	1770 (+90.7%)	1390 (+50.1%)	1040 (+12.3%)
Côte d'Ivoire (CIV)	5150 (+0%)	11700 (+127.2%)	14600 (+182.8%)	11900 (+130.8%)	8540 (+65.7%)	3970 (-22.9%)	8970 (+74.2%)	11200 (+116.8%)	9140 (+77.4%)	6650 (+29.1%)
El Salvador (SLV)	475 (+0%)	1020 (+115.3%)	1250 (+164%)	1040 (+119.9%)	764 (+60.9%)	368 (-22.5%)	786 (+65.6%)	963 (+102.8%)	805 (+69.7%)	601 (+26.7%)
Chile (CHL)	1960 (+0%)	3110 (+58.7%)	3530 (+80%)	2340 (+19.7%)	1810 (-7.5%)	1590 (-18.6%)	2470 (+26.2%)	2780 (+41.8%)	1850 (-5.5%)	1430 (-26.8%)
Sri Lanka (LKA)	72.5 (+0%)	89 (+22.8%)	93.2 (+28.6%)	80 (+10.4%)	71.8 (-0.8%)	62.4 (-13.9%)	75.6 (+4.4%)	78.8 (+8.8%)	68.3 (-5.7%)	61.8 (-14.7%)
Uruguay (URY)	5200 (+0%)	4970 (-4.2%)	6120 (+17.9%)	70 (-98.7%)	2570 (-50.6%)	4360 (-16.1%)	4050 (-22.1%)	4900 (-5.7%)	53.9 (-99%)	2040 (-60.8%)
India (IND)	1000 (+0%)	1330 (+33.4%)	1420 (+42.4%)	1160 (+16.2%)	1040 (+4.2%)	826 (-17.4%)	1090 (+8.9%)	1160 (+15.8%)	954 (-4.7%)	869 (-13.2%)
Malaysia (MYS)	181 (+0%)	407 (+125.1%)	503 (+178.2%)	413 (+128.5%)	295 (+62.8%)	140 (-22.8%)	313 (+72.9%)	386 (+113.5%)	318 (+76%)	230 (+27%)
Other	6580 (+0%)	10400 (+71.2%)	11700 (+102.7%)	9920 (+73.8%)	8260 (+33.1%)	5340 (-18.9%)	8270 (+34.1%)	9250 (+57.2%)	7900 (+36%)	6690 (+6.9%)

Table S5. Virtual biodiversity threats imported to the United States by foreign country across scenarios

This table shows the total biodiversity threat caused in each of the United States' trading partners by production of food consumed in the United States in 2012, in units of potential global species extinctions, summed across all agricultural land use types and taxonomic groups threatened. Only the top 20 trading partners, sorted in descending order by the size of the biodiversity threat they virtually exported to the United States in 2012 (baseline scenario) are listed. The remaining countries are aggregated into the category "Other," which accounts for less than 2% of the United States' virtual biodiversity threat imports. For each of the 20 countries, the value for the baseline scenario and the nine other counterfactual scenarios is provided (the baseline diet and four alternative diets crossed with baseline levels of food waste and 50% food waste reduction). After each value, the percentage change in each scenario relative to the baseline case is listed in parentheses.

	No waste reduction					50% waste reduction				
	baseline diet	USDA U.S. style	USDA Mediterranean	USDA vegetarian	Planetary Health	baseline diet	USDA U.S. style	USDA Mediterranean	USDA vegetarian	Planetary Health
Australia (AUS)	42.7 (+0%)	40.7 (-4.6%)	50.2 (+17.5%)	0.262 (-99.4%)	21 (-50.8%)	35.8 (-16.1%)	33.1 (-22.4%)	40.1 (-6%)	0.194 (-99.5%)	16.7 (-61%)
Mexico (MEX)	36.9 (+0%)	50.3 (+36.4%)	59.7 (+62%)	28.7 (-21.8%)	30.4 (-17.6%)	30.2 (-18.2%)	40 (+8.5%)	47.1 (+27.7%)	22.5 (-38.8%)	24 (-35%)
Canada (CAN)	21.2 (+0%)	21.7 (+2.7%)	25.1 (+18.7%)	7.61 (-64%)	15.1 (-28.5%)	17.6 (-16.6%)	17.7 (-16.3%)	20.2 (-4.4%)	6.23 (-70.5%)	12.2 (-42.3%)
Colombia (COL)	15.7 (+0%)	35.5 (+125.8%)	44.1 (+180.7%)	36 (+129.2%)	25.9 (+64.9%)	12.1 (-22.9%)	27.2 (+73.3%)	33.8 (+115.2%)	27.7 (+76.2%)	20.2 (+28.5%)
Ecuador (ECU)	12.7 (+0%)	28.7 (+125.9%)	35.6 (+180.7%)	29.1 (+129.5%)	20.9 (+64.8%)	9.8 (-22.9%)	22 (+73.4%)	27.3 (+115.3%)	22.4 (+76.5%)	16.3 (+28.4%)
Nicaragua (NIC)	10.1 (+0%)	11.6 (+15.1%)	14.1 (+40%)	3.85 (-61.5%)	6.76 (-32.7%)	8.34 (-17.1%)	9.28 (-7.7%)	11.2 (+10.9%)	3 (-70.1%)	5.35 (-46.8%)
New Zealand (NZL)	7.83 (+0%)	7.61 (-2.7%)	9.27 (+18.5%)	0.354 (-95.5%)	3.89 (-50.3%)	6.57 (-16.1%)	6.19 (-20.9%)	7.42 (-5.2%)	0.286 (-96.3%)	3.09 (-60.5%)
Costa Rica (CRI)	5.58 (+0%)	10.7 (+91.5%)	13 (+133.7%)	9.62 (+72.4%)	7.39 (+32.5%)	4.4 (-21.1%)	8.28 (+48.5%)	10.1 (+80.6%)	7.43 (+33.1%)	5.78 (+3.7%)
Guatemala (GTM)	5.17 (+0%)	11.3 (+117.9%)	13.6 (+162.6%)	11.4 (+120.8%)	7.88 (+52.5%)	4 (-22.5%)	8.7 (+68.3%)	10.5 (+102.5%)	8.83 (+70.9%)	6.16 (+19.2%)
Indonesia (IDN)	2.54 (+0%)	4.97 (+95.9%)	5.93 (+133.8%)	4.87 (+92%)	3.58 (+41.3%)	2 (-21%)	3.87 (+52.8%)	4.61 (+81.7%)	3.8 (+49.9%)	2.84 (+12.1%)
Peru (PER)	2.51 (+0%)	5.11 (+103.7%)	5.88 (+134.3%)	5.17 (+106.1%)	3.48 (+38.5%)	1.98 (-21%)	4.01 (+59.7%)	4.59 (+82.8%)	4.06 (+61.8%)	2.75 (+9.4%)
Brazil (BRA)	1.86 (+0%)	2.69 (+44.4%)	3.29 (+77%)	1.68 (-9.7%)	1.76 (-5.4%)	1.51 (-18.6%)	2.12 (+13.7%)	2.57 (+38.3%)	1.3 (-30.2%)	1.38 (-25.6%)
Honduras (HND)	1.86 (+0%)	3.8 (+104.4%)	4.63 (+149.1%)	3.65 (+96.7%)	2.69 (+44.8%)	1.45 (-21.8%)	2.94 (+58%)	3.57 (+92.1%)	2.82 (+51.9%)	2.11 (+13.4%)
Côte d'Ivoire (CIV)	1.63 (+0%)	3.7 (+127.2%)	4.61 (+182.8%)	3.76 (+130.8%)	2.7 (+65.8%)	1.26 (-22.9%)	2.84 (+74.2%)	3.53 (+116.8%)	2.89 (+77.4%)	2.1 (+29.1%)
El Salvador (SLV)	0.906 (+0%)	1.95 (+115.4%)	2.39 (+164.1%)	1.99 (+120%)	1.46 (+61%)	0.702 (-22.5%)	1.5 (+65.7%)	1.84 (+102.9%)	1.54 (+69.7%)	1.15 (+26.7%)
Chile (CHL)	0.803 (+0%)	1.34 (+66.8%)	1.54 (+92.3%)	1.07 (+33.1%)	0.815 (+1.6%)	0.649 (-19.2%)	1.06 (+31.8%)	1.21 (+50.8%)	0.837 (+4.4%)	0.643 (-19.9%)
Sri Lanka (LKA)	0.552 (+0%)	0.677 (+22.7%)	0.709 (+28.5%)	0.608 (+10.2%)	0.546 (-1%)	0.475 (-13.8%)	0.575 (+4.3%)	0.599 (+8.7%)	0.52 (-5.8%)	0.47 (-14.7%)
Uruguay (URY)	0.585 (+0%)	0.56 (-4.2%)	0.689 (+17.9%)	0.008 (-98.6%)	0.289 (-50.6%)	0.491 (-16.1%)	0.455 (-22.1%)	0.551 (-5.7%)	0.00616 (-98.9%)	0.229 (-60.8%)
India (IND)	0.405 (+0%)	0.541 (+33.5%)	0.578 (+42.7%)	0.472 (+16.5%)	0.422 (+4.3%)	0.335 (-17.4%)	0.442 (+9.1%)	0.47 (+16%)	0.387 (-4.5%)	0.352 (-13.1%)
Malaysia (MYS)	0.343 (+0%)	0.774 (+125.4%)	0.958 (+179.1%)	0.786 (+128.9%)	0.561 (+63.6%)	0.265 (-22.8%)	0.594 (+73.1%)	0.735 (+114.2%)	0.605 (+76.2%)	0.438 (+27.6%)
Other	2.43 (+0%)	4.18 (+82.4%)	4.71 (+113.7%)	4.13 (+84.2%)	3.12 (+35.6%)	1.95 (-19.5%)	3.31 (+42.7%)	3.7 (+65.8%)	3.27 (+44.2%)	2.52 (+9.1%)

Table S6. Virtual imports of biodiversity threats into the United States by taxonomic group, baseline scenario

This table shows the total biodiversity threat caused in each of the United States' trading partners by production of food consumed in the United States in 2012, in units of potential global species extinctions, in the baseline scenario, summed across all agricultural land use types but disaggregated by taxonomic group threatened. Only the top 20 trading partners, sorted in descending order by the size of the biodiversity threat they virtually exported to the United States in 2012 (baseline scenario) are listed. The remaining countries are aggregated into the category "Other," which accounts for less than 2% of the United States' virtual biodiversity threat imports.

	Virtual biodiversity threat export by taxonomic group						
	plants	amphibians	birds	mammals	reptiles	animals	total
Australia (AUS)	16.4000	0.7990	1.36000	0.89400	0.24700	3.3000	19.700
Mexico (MEX)	12.1000	1.8800	0.67600	0.80500	0.83300	4.2000	16.300
Canada (CAN)	9.2000	0.1530	0.26300	0.38200	0.11700	0.9150	10.100
Colombia (COL)	5.2100	1.1700	0.36100	0.19100	0.04280	1.7700	6.980
Ecuador (ECU)	4.2000	0.9380	0.32300	0.13900	0.03000	1.4300	5.630
Nicaragua (NIC)	2.8600	0.9710	0.27900	0.14900	0.04770	1.4500	4.310
New Zealand (NZL)	3.3300	0.0283	0.32100	0.00915	0.02840	0.3870	3.720
Costa Rica (CRI)	1.8400	0.4200	0.12700	0.07750	0.00611	0.6310	2.470
Guatemala (GTM)	1.5700	0.4420	0.08340	0.07900	0.06960	0.6740	2.250
Indonesia (IDN)	0.8080	0.0586	0.10200	0.11500	0.03050	0.3070	1.110
Peru (PER)	0.5910	0.2570	0.12600	0.04990	0.00965	0.4430	1.030
Brazil (BRA)	0.4750	0.1460	0.08980	0.06010	0.00722	0.3040	0.778
Honduras (HND)	0.4550	0.2040	0.04390	0.04190	0.02670	0.3160	0.771
Côte d'Ivoire (CIV)	0.2460	0.1300	0.08270	0.12500	0.04160	0.3800	0.625
El Salvador (SLV)	0.2320	0.0910	0.02200	0.02120	0.01330	0.1480	0.379
Chile (CHL)	0.2760	0.0380	0.01490	0.02460	0.00612	0.0836	0.360
Sri Lanka (LKA)	0.1910	0.0359	0.00751	0.00851	0.00438	0.0563	0.248
Uruguay (URY)	0.0767	0.0458	0.04800	0.04540	0.00452	0.1440	0.220
India (IND)	0.1410	0.0166	0.00976	0.00584	0.00892	0.0412	0.182
Malaysia (MYS)	0.1190	0.0135	0.00615	0.01050	0.00492	0.0351	0.154
Other	0.8370	0.0830	0.06610	0.07850	0.02320	0.2510	1.090

Table S7. Foreign imports of goods and associated virtual land imports into the United States, baseline scenario

This table contains the quantity of each type of agricultural good, by weight in tonnes, reported by FAOSTAT that each of the United States' trading partners exported to the United States in 2012, in the baseline scenario. The table also lists the virtual land export in square kilometers associated with each of these goods, summed across all land use types (e.g., for beef cattle, the sum of the virtual pastureland export and virtual cropland export due to crops grown for cattle feed). Only the top 20 biodiversity threat exporters to the United States are shown; the remainder are aggregated into the "Other" category (see caption of Table S3). Within each country, goods are sorted in descending order by virtual land export. Goods with less than 1000 tonnes exported are summed into the "Other" category. The names of each good follow FAOSTAT's classification.

item	export quantity tonnes	virtual land export km^2
Australia (AUS)		
meat, cattle	321000	205000
meat, sheep	71400	61200
meat, goat	17800	18500
milk, cattle	8530	269
chick peas	3600	26.7
meat, pig	2640	13.3
molasses	71300	8.93
nuts nes	1200	6.79
oranges	6410	3.28
tangerines, mandarins, clementines, satsumas	3630	1.59
sugar nes	4700	0.589
sugar confectionery	2280	0.286
other	3830	22.3
Mexico (MEX)		
meat, cattle	168000	33400
coffee, green	59500	2250
vegetables, fresh nes	561000	662
avocados	678000	656
chillies and peppers, green	939000	516
milk, cattle	40400	463
lemons and limes	599000	413
tomatoes	1670000	385
mangoes, mangosteens, guavas	315000	309
beans, dry	23000	297
pumpkins, squash and gourds	475000	256
watermelons	697000	223
walnuts, with shell	26500	162
asparagus	141000	158
cucumbers and gherkins	690000	145
cauliflowers and broccoli	231000	138
chillies and peppers, dry	25500	135
maize	46700	129
onions, dry	374000	122
grapes	161000	120
bananas	350000	119
sugar raw centrifugal	728000	99.5
lettuce and chicory	175000	78.3
sugar refined	482000	65.9
beans, green	45100	53
chick peas	9390	52.8
fruit, fresh nes	37700	49.3
beer of barley	2550000	45.4
meat, pig	15700	43.8
cabbages and other brassicas	148000	43.5
melons, other (inc.cantaloupes)	125000	41.7
wheat	19800	38.8
oranges	55600	38.7
carrots and turnips	105000	37.4
sugar confectionery	256000	35
peas, green	17800	34.3
coconuts	17500	27.6
papayas	152000	26.7

(continued)

item	export quantity tonnes	virtual land export km^2
strawberries	112000	24.9
olives	6440	17.6
pineapples	73200	16
molasses	102000	14
groundnuts, shelled	1920	11.5
roots and tubers nes	32600	10.8
garlic	11200	9.57
spinach	13700	8.7
eggplants (aubergines)	62900	8.63
meat, chicken	3960	7.18
sorghum	2100	5.96
oilseeds nes	5060	5.61
spices nes	4580	5.56
dates	3030	4.97
leeks, other alliaceous vegetables	7220	4.33
fructose and syrup, other	26300	3.59
tangerines, mandarins, clementines, satsumas	4070	2.8
sweet potatoes	5310	2.71
grapefruit (inc. pomelos)	3430	1.35
artichokes	1590	1.23
eggs, chicken	1320	0.321
sugar nes	1450	0.198
other	5270	83
Canada (CAN)		
meat, cattle	342000	47900
wheat	2750000	8560
oats	1530000	4540
meat, pig	396000	3180
peas, dry	2e+05	802
barley	272000	760
meat, chicken	64600	511
maize	495000	494
milk, cattle	99400	448
rye	117000	402
beans, dry	79900	342
lentils	43900	296
meat, horse	1120	261
chick peas	32700	187
potatoes	504000	118
blueberries	35100	79.9
canary seed	8270	62.3
anise, badian, fennel, coriander	4250	48.6
cabbages and other brassicas	68300	31.5
chillies and peppers, green	138000	26.2
cucumbers and gherkins	139000	25.3
tomatoes	182000	24.8
cranberries	61400	23.7
carrots and turnips	89800	20.8
buckwheat	3690	19.6
triticale	5090	17.8
lettuce and chicory	39500	17.5
onions, dry	66600	15.2
pumpkins, squash and gourds	23600	11.9
apples	27000	10.1
vegetables, fresh nes	25900	9.82
sugar beet	57200	8.37
cauliflowers and broccoli	15500	8.36
beans, green	4910	7.06
eggs, chicken	8760	6.67
cherries	5090	4.62
asparagus	1470	3.36
spinach	2520	2.87
grapes	1250	1.31
other	3640	15.7
Colombia (COL)		
coffee, green	297000	3040
bananas	325000	114
plantains and others	61500	70.4

(continued)

item	export quantity tonnes	virtual land export km^2
sugar raw centrifugal	47400	5.32
sugar refined	46500	5.22
molasses	35600	3.99
lemons and limes	4380	3.15
sugar confectionery	12800	1.44
roots and tubers nes	1240	1.29
pineapples	1430	0.343
other	4380	51.8
Ecuador (ECU)		
cocoa, beans	67900	1580
bananas	809000	211
plantains and others	127000	186
coffee, green	2150	147
mangoes, mangosteens, guavas	46600	79.8
roots and tubers nes	2950	10.7
pepper (piper spp.)	1030	5.12
cassava dried	1010	1.87
cauliflowers and broccoli	1160	1.5
sugar raw centrifugal	10300	1.21
pineapples	2830	0.774
other	5320	23.4
Nicaragua (NIC)		
meat, cattle	46400	4620
coffee, green	63200	675
beans, dry	9940	132
milk, cattle	4730	121
sugar raw centrifugal	70300	7.62
plantains and others	11700	7.01
bananas	38900	6.3
molasses	49400	5.35
sugar nes	32900	3.56
vegetables, fresh nes	1860	1.91
sugar refined	12000	1.3
other	2540	6.59
New Zealand (NZL)		
meat, cattle	206000	7350
meat, sheep	27800	1200
milk, cattle	126000	177
apples	42300	8.14
kiwi fruit	17500	5.06
beer of barley	1790	3.02
onions, shallots, green	1680	0.397
pears	1470	0.29
other	3820	18.1
Costa Rica (CRI)		
meat, cattle	9580	370
coffee, green	35600	328
bananas	868000	165
pineapples	1080000	150
cassava dried	75500	50.4
melons, other (inc.cantaloupes)	60200	19
vegetables, fresh nes	24400	15.9
sugar raw centrifugal	77700	11.6
molasses	24200	3.6
chillies and peppers, green	1380	2.11
mangoes, mangosteens, guavas	1590	2.03
ginger	2280	1.97
plantains and others	1490	1.39
watermelons	5830	1.37
fruit, tropical fresh nes	1060	1.26
roots and tubers nes	1230	0.981
carrots and turnips	1310	0.383
sugar refined	1510	0.225
other	4330	14.1
Guatemala (GTM)		
coffee, green	74000	864
bananas	1930000	392

(continued)

item	export quantity tonnes	virtual land export km^2
melons, other (inc.cantaloupes)	382000	168
beans, green	21000	102
plantains and others	135000	63.7
peas, green	23600	31
sugar raw centrifugal	261000	21.6
watermelons	62700	16.1
mangoes, mangosteens, guavas	17600	13.7
beans, dry	1040	9.98
papayas	28400	9.65
cauliflowers and broccoli	14700	8.92
molasses	94300	7.82
pineapples	21500	7.73
vegetables, fresh nes	5110	6.39
fruit, fresh nes	2850	5.23
tomatoes	9980	2.64
sugar refined	29400	2.44
chillies and peppers, green	5100	2.07
lemons and limes	2480	1.16
carrots and turnips	3110	1.06
sugar non-centrifugal	8030	0.666
cabbages and other brassicas	1380	0.433
onions, dry	1220	0.41
sugar nes	4490	0.372
sugar confectionery	1820	0.151
other	2850	23.4
Indonesia (IDN)		
coffee, green	66600	1240
cinnamon (cannella)	21800	267
pepper (piper spp.)	7500	153
nutmeg, mace and cardamoms	1470	75.9
sugar nes	16200	61.1
milk, cattle	2670	46.8
tea	3750	30.5
sugar confectionery	3170	12
other	3200	57.7
Peru (PER)		
coffee, green	54800	750
milk, cattle	22700	433
quinoa	17400	129
asparagus	88900	76.7
avocados	58800	49.8
cocoa, beans	3340	40.9
grapes	80800	36.8
mangoes, mangosteens, guavas	44900	34.8
onions, dry	119000	29.6
chillies and peppers, dry	16400	26.9
bananas	60500	21.8
tangerines, mandarins, clementines, satsumas	45700	17.1
beer of barley	1380	16.5
blueberries	16100	15.9
beans, dry	1280	10.8
peas, green	2960	7.75
maize	1580	4.82
ginger	6900	4.49
oilseeds nes	1230	4.46
sugar raw centrifugal	47800	3.97
flour, cassava	1400	1.15
sugar refined	1010	0.0836
other	5440	13.1
Brazil (BRA)		
meat, cattle	32600	3280
coffee, green	369000	2420
maize	119000	231
milk, cattle	3450	55
pepper (piper spp.)	10800	42.8
sugar raw centrifugal	212000	28.7
mangoes, mangosteens, guavas	29600	15.8

(continued)

item	export quantity tonnes	virtual land export km^2
sugar refined	96800	13.1
meat, pig	4120	8
flour, cassava	4870	3.27
sugar confectionery	13700	1.86
starch, cassava	2420	1.62
sugar nes	11300	1.53
roots and tubers nes	1200	1.23
papayas	2950	0.689
grapes	1100	0.57
melons, other (inc.cantaloupes)	1060	0.421
molasses	2420	0.328
other	2740	8.28
Honduras (HND)		
coffee, green	62000	550
bananas	594000	120
meat, cattle	1260	114
melons, other (inc.cantaloupes)	158000	35.8
beans, dry	1220	15.7
vegetables, fresh nes	19000	13.1
molasses	105000	12.7
pineapples	51400	11.3
watermelons	33500	7.88
cucumbers and gherkins	25500	6.01
chillies and peppers, green	14400	5.7
sugar raw centrifugal	26000	3.13
eggplants (aubergines)	9880	3.11
pumpkins, squash and gourds	11100	2.77
cassava dried	1860	2.19
sugar refined	13500	1.62
lemons and limes	1610	0.793
sugar nes	2130	0.256
other	4290	23.5
Côte d'Ivoire (CIV)		
cocoa, beans	262000	5130
other	1200	21.1
El Salvador (SLV)		
coffee, green	14600	423
molasses	160000	18.4
sugar raw centrifugal	106000	12.2
sugar refined	15300	1.76
plantains and others	2680	1.41
chillies and peppers, green	1700	0.614
other	2760	16.9
Chile (CHL)		
milk, cattle	23500	450
grapes	330000	289
cranberries	61300	96.3
avocados	28000	60.1
tangerines, mandarins, clementines, satsumas	97700	54.8
oranges	67300	37.2
meat, chicken	33000	25.7
maize	23700	20.6
apples	91600	18.9
peaches and nectarines	36900	18.5
lemons and limes	36200	16
plums and sloes	23000	13.6
cherries	6960	13.6
kiwi fruit	25400	9.9
fruit, fresh nes	3860	8.57
pears	15500	4.6
meat, pig	1690	0.903
onions, dry	3210	0.667
other	4250	820
Sri Lanka (LKA)		
tea	4720	32.1
cinnamon (cannella)	2070	28.7
other	1430	11.7

(continued)

item	export quantity tonnes	virtual land export km^2
Uruguay (URY)		
meat, cattle	47000	5140
milk, cattle	1590	14.9
tangerines, mandarins, clementines, satsumas	12600	7.66
oranges	2210	1.25
lemons and limes	1520	0.727
other	1560	29
India (IND)		
anise, badian, fennel, coriander	15000	201
pepper (piper spp.)	9650	200
chillies and peppers, dry	25000	117
beans, dry	3890	90.5
spices nes	18500	89.8
oilseeds nes	11300	81.9
tea	14200	66.7
meat, cattle	2880	39
chick peas	2610	28.3
coffee, green	2130	28.1
maize	2710	9.71
mangoes, mangosteens, guavas	5580	6.54
ginger	1520	2.65
milk, cattle	1390	1.52
sugar raw centrifugal	6820	0.943
sugar refined	6110	0.844
molasses	1640	0.226
sugar confectionery	1020	0.141
other	5200	36.2
Malaysia (MYS)		
cocoa, beans	1780	174
milk, cattle	1230	4.43
sugar confectionery	1050	0.493
other	1000	1.54
Other		
cocoa, beans	75700	1690
coffee, green	72400	1220
meat, pig	115000	518
milk, cattle	229000	479
tea	77900	443
maize	235000	348
wheat	119000	341
beer of barley	122000	340
oats	103000	288
rye	126000	282
quinoa	16800	274
oilseeds nes	32400	262
beans, dry	30400	216
meat, cattle	4000	178
barley	43300	161
sorghum	53500	126
chick peas	9210	85.4
anise, badian, fennel, coriander	6270	82
sugar raw centrifugal	437000	74.3
spices nes	12700	57
ginger	55800	55.6
coconuts	25900	55.5
chillies and peppers, dry	28000	47
tangerines, mandarins, clementines, satsumas	81100	41.4
starch, cassava	88000	39.9
garlic	74300	38
dates	20800	37
peas, dry	6050	28.8
pears	64200	28
nuts nes	11200	27.6
vegetables, fresh nes	10300	22.6
lentils	2940	20.6
hops	3550	19.9
oranges	54100	15.3

(continued)

item	export quantity tonnes	virtual land export km^2
groundnuts, shelled	2750	14.7
molasses	72100	14.2
chestnut	3390	13.4
kiwi fruit	26600	12.2
eggs, chicken	22400	8.9
mangoes, mangosteens, guavas	4330	8.81
sugar confectionery	84500	8.27
plantains and others	7690	7.38
fruit, fresh nes	6180	6.83
apples	13300	5.78
roots and tubers nes	9580	5.44
olives	3610	4.65
lemons and limes	13000	4.65
broad beans, horse beans, dry	1400	4.34
meat, chicken	6880	4.21
sugar refined	20400	3.78
onions, dry	12200	3.54
chillies and peppers, green	26000	2.85
rice, paddy	1380	2.82
sugar nes	18000	2.51
carrots and turnips	16300	2.44
onions, shallots, green	4040	1.85
grapes	1780	1.79
cassava dried	2280	1.61
papayas	8820	1.41
pineapples	5990	1.39
persimmons	2770	1.28
beans, green	1260	1.27
grapefruit (inc. pomelos)	4460	1.27
bananas	2730	1.18
sweet potatoes	1310	0.968
flour, cassava	1560	0.745
mushrooms and truffles	13500	0.662
potatoes	1750	0.539
lettuce and chicory	1940	0.518
fructose and syrup, other	2850	0.436
cabbages and other brassicas	1030	0.329
cucumbers and gherkins	3370	0.237
eggplants (aubergines)	1750	0.0811
other	13000	367

Table S8. Data sources

The following table contains the data sources used in the manuscript, along with the names of the dataset providers, the year the datasets represent, a description of the use of the datasets in the analysis, URLs of the datasets and when the datasets were downloaded and last checked for online availability. The table lists primary non-spatial data sources, spatial data sources (polygon and raster), and crosswalk tables used to harmonize different datasets. Some crosswalk tables were downloaded from existing sources and some were created manually by the authors for this analysis. Citations for each data source are provided in the *SI References* section at the bottom of this document, numbered corresponding to the numbers in the "Citation" column of the table.

Dataset name	Dataset provider	Data years	Description	Location on web	Date down-loaded	Date most recently checked	Citation
Primary data							
USEEIOv2.0-alpha input-output model	U.S. Environmental Protection Agency, derived from data provided by U.S. Bureau of Economic Analysis	2012	Direct requirements coefficients matrix and personal consumption expenditure vector from input-output model	click here	2021-03-23	2021-03-23	34
Census of Agriculture	U.S. Department of Agriculture, National Agricultural Statistics Service	2012	Data on crop and livestock production value and weight, and area harvested, by state and county	click here	2019-10-24	2021-03-30	28
County Business Patterns	U.S. Census Bureau	2012	Number of establishments, employees, and total payroll for industries classified by NAICS code for each USA county	click here	2019-02-11	2021-03-30	25
Statistics of U.S. Businesses	U.S. Census Bureau	2012	Number of establishments, employees, payroll, and total receipts for industries classified by NAICS code for each USA state	click here	2019-02-11	2021-03-30	27
2015-2020 Dietary Guidelines	U.S. Department of Agriculture	—	Data from Appendices 3-5 of 2015-2020 Dietary Guidelines for Americans, manually copied and saved to CSV (calories per day or servings per day of each food group on recommended diets)	click here	2021-04-20	2021-04-20	29
Planetary Health diet	EAT Lancet Commission	—	Data copied directly from report and saved to CSV (calories per day of each food group on planetary health diet)	click here	2020-12-08	2021-03-30	33
Loss-Adjusted Food Availability Data Series	U.S. Department of Agriculture, Economic Research Service	multiple	Relative percentage losses for 200 food items at different stages of the food supply chain, and the total amount of each food item available for consumption per capita daily in the USA, in units of calories and servings	click here	2020-12-09	2021-03-30	1
Quarterly Food-at-home Price Database, version 2	U.S. Department of Agriculture, Economic Research Service	2010	Relative prices per unit weight for 40 food items averaged across different regions of the USA	click here	2019-03-14	2021-03-30	30
FAOSTAT	United Nations Food and Agriculture Organization	2013-2017	All data available from FAOSTAT (global agriculture data)	click here	2020-08-31	2021-03-30	9
U.S. County Personal Income	Supplementary information from Lin et al. 2019, derived from U.S. Bureau of Economic Analysis	2012	Total personal income of each USA county	click here	2021-04-19	2021-04-19	24

(continued)

Dataset name	Dataset provider	Data years	Description	Location on web	Date downloaded	Date most recently checked	Citation
Biodiversity characterization factors	Chaudhary & Brooks 2018, derived from multiple data sources	multiple	Potential species lost per unit of land converted to human use, across ecoregions, taxa, and land use types	click here	2020-12-07	2021-03-30	3
Spatial data							
The Nature Conservancy terrestrial ecoregions	The Nature Conservancy	2009	Polygon file with all boundaries of terrestrial ecoregions globally	click here	2018-10-15	2021-03-29	17
United States county boundaries shapefile	U.S. Census Bureau	2014	Polygon file of the United States county boundaries as they existed in 2014	No longer available. A similar file is available here.	2017-11-30	—	26
Global country administrative boundaries shapefile	Natural Earth	2020	Polygon file of all country boundaries as they existed in 2018	click here	2020-09-16	2021-03-29	15
National Land Cover Database 2016, CONUS	Multresolution Land Characteristics Consortium	2016	Raster at 30m resolution of modeled land cover classes in contiguous United States	click here	2019-09-16	2021-03-29	6
National Land Cover Database 2016, Alaska	Multresolution Land Characteristics Consortium	2016	Raster at 30m resolution of modeled land cover classes in Alaska	click here	2021-02-04	2021-03-29	6
NOAA Land Cover Dataset 2001, Hawaii	Multresolution Land Characteristics Consortium	2001	Raster at 30m resolution of modeled land cover classes in Hawaii	click here	2021-02-04	2021-03-29	14
Global Agricultural Lands: Pastures v1	SEDAC CIESIN, Columbia University	2000	Raster at 1km resolution of global pastureland	click here	2020-09-16	2021-03-29	20
Crop Dominance 2010 Global 1 km	Global Food Security Support Analysis Data (GFSAD)	2010	Raster at 1km resolution of global irrigated and rainfed cropland	click here	2020-09-16	2021-03-29	23
U.S. Census Grids: Summary File 1, v1	SEDAC CIESIN, Columbia University	2010	Gridded product including population totals from 2010 census at 1 km resolution. Separate files for contiguous USA, Hawaii, Alaska, and Aleutian islands	click here	2020-08-14	2021-03-29	2
Crosswalks							
FIPS codes harmonization between Census Tiger shapefile and county personal income data	None (created manually)	—	For combining map polygons of county map to match the income data otherwise used to downscale data to county level	—	—	—	—
Weight in pounds per bushel of grain and oilseed crops	Rayglen	—	For converting grain and oilseed production value to weight, to disaggregate grain from oilseed production values	click here	2019-12-06	2021-06-01	21
Price per bushel or hundredweight of grain and oilseed crops in 2014-2016	U.S. Department of Agriculture, Economic Research Service	2014-2016	For converting grain and oilseed production value to weight, to disaggregate grain from oilseed production values	click here	2019-12-06	2021-06-01	32
FAOSTAT category hierarchical structure	United Nations Food and Agriculture Organization	—	Identifies which FAOSTAT codes represent aggregations of individual items. Aggregates are removed from analysis.	click here	2020-11-17	2021-06-01	9
NAICS codes to BEA codes	U.S. EPA USEEIO model (useeior package)	2012	Harmonizes NAICS2012 codes (used in NASS Census of Agriculture, SUSB, and CBP datasets) with BEA codes (used in input-output tables). Typically many-to-one NAICS-BEA mapping	click here	2021-03-23	2021-03-23	34

(continued)

Dataset name	Dataset provider	Data years	Description	Location on web	Date down-loaded	Date most recently checked	Citation
LAFA food categories to Lancet and USDA dietary guidelines food groups	None (created manually)	—	Maps LAFA foods to dietary guideline food groups for Lancet and USDA diets so that waste and diet scenarios can be combined. Typically many-to-one LAFA-diet mapping	—	—	—	—
FAOSTAT commodity codes in trade dataset to FAOSTAT commodity codes in production dataset	None (created manually)	—	Harmonizes the FAOSTAT codes in the crop and livestock production data by country with the codes in the international trade data, used to determine the proportion of each product exported to the United States	—	—	—	—
FAOSTAT commodity codes to FAO food balance sheet commodity codes	None (created manually)	—	Harmonizes the FAOSTAT codes in the crop and livestock production data by country with the food balance sheet commodity codes, used to determine the proportion of each crop that is used for feed that feeds livestock exported to the United States	—	—	—	—
QFAHPD food categories to LAFA food categories	None (created manually)	—	Harmonizes QFAHPD food categories with LAFA food categories, used to convert loss rates by weight to loss rates by monetary value. Typically one-to-many mapping QFAHPD to LAFA.	—	—	—	—
LAFA food categories to QFAHPD food categories to BEA codes	None (created manually)	—	Harmonizes LAFA to QFAHPD to BEA codes, used to convert loss rates by weight to monetary value. Typically one-to-many mapping for QFAHPD-LAFA and QFAHPD-BEA.	—	—	—	—
LAFA category hierarchical structure	None (created manually)	—	Identifies which LAFA food groups represent aggregations of individual items. Aggregates are removed from analysis.	—	—	—	—
BEA codes to LAFA food categories	None (created manually)	—	Harmonizes BEA codes to LAFA food categories. Typically one-to-many mapping BEA-LAFA. Used to convert scenario consumption factors for LAFA categories to BEA codes.	—	—	—	—

Table S9: Primary agricultural commodity and processed food commodity codes

The following table contains the commodity names and six-character codes from the U.S. Bureau of Economic Analysis input-output tables used in our analysis. Thirty-seven commodities are shown, including both primary agricultural goods (codes beginning with `1`) and processed foods (codes beginning with `3`).

Commodity code	Commodity description
primary agricultural goods	
1111A0	Fresh soybeans, canola, flaxseeds, and other oilseeds
1111B0	Fresh wheat, corn, rice, and other grains
111200	Fresh vegetables, melons, and potatoes
111300	Fresh fruits and tree nuts
111400	Greenhouse crops, mushrooms, nurseries, and flowers
111900	Tobacco, cotton, sugarcane, peanuts, sugar beets, herbs and spices, and other crops
112120	Dairies
1121A0	Cattle ranches and feedlots
112300	Poultry farms
112A00	Animal farms and aquaculture ponds (except cattle and poultry)
114000	Wild-caught fish and game
processed foods	
311210	Flours and malts
311221	Corn products
311224	Vegetable oils and by-products
311225	Refined vegetable, olive, and seed oils
311230	Breakfast cereals
311300	Sugar, candy, and chocolate
311410	Frozen food
311420	Fruit and vegetable preservation
311513	Cheese
311514	Dry, condensed, and evaporated dairy
31151A	Fluid milk and butter
311520	Ice cream and frozen desserts
311615	Packaged poultry
31161A	Packaged meat (except poultry)
311700	Seafood
311810	Bread and other baked goods
3118A0	Cookies, crackers, pastas, and tortillas
311910	Snack foods
311940	Seasonings and dressings
311990	All other foods
311930	Flavored drink concentrates
312110	Soft drinks, bottled water, and ice
311920	Coffee and tea
312120	Breweries and beer
312130	Wineries and wine
312140	Distilleries and spirits

Appendix 4: Comparison of land footprint estimates with previous study

Summary

This appendix is a supplement to the manuscript "Biodiversity effects of food system sustainability actions from farm to fork" by Quentin D. Read, Kelly L. Hondula, and Mary K. Muth.

In this appendix, which contains R code and results, we compare the land footprint estimates generated by our own models with the estimates generated by Laroche et al. (2020). We describe how we harmonized our results with theirs and present a figure and table comparing the results. Overall, we found that our study estimated higher land footprints than Laroche and colleagues'. In both studies, the relative differences between diets are qualitatively very similar. However, Laroche et al. estimated the reduction in land footprint, especially foreign-sourced, due to diet shifts to be much greater than we did.

Harmonization

Laroche et al. provide estimates of the per capita land footprint of the average American diet and of several other diets. They provide totals for domestic and imported (outsourced in their terminology) land footprint, and they further disaggregate the foreign land footprint into cropland and grassland. These estimates are given in Table 3 of their manuscript.

We assumed that their term grassland corresponds to our definition of pastureland, and that their term cropland corresponds to the total of our annual cropland and permanent cropland categories.

In the following code, we load the data and then sum up our estimates by origin and land type, renaming them to use the same terminology as Laroche et al. (`foreign` becomes `outsourced` and `pasture` becomes `grassland`, and `cropland` is the sum of `annual` and `permanent`). We also divide our estimate by the 2012 USA population to make it a per capita estimate matching Laroche et al., and convert our units from square kilometers to square meters.

```
library(data.table)
library(ggplot2)
library(dplyr)
library(purrr)
library(kableExtra)
library(scales)

load(file.path(final_output_path, 'all_app_data.RData'))

laroche_landuse <- fread(file.path(raw_data_path, 'biodiversity/laroche2020_table3.csv'))

# Sum up the land footprint by origin x land type
landflow_cols <- c('flow_inbound_total', 'flow_inbound_foreign')
our_landuse <- county_land_flow_sums[, lapply(.SD, sum),
                                     by = .(scenario_diet, scenario_waste, land_type),
                                     .SDcols = landflow_cols]
setnames(our_landuse, old = landflow_cols, new = c('total', 'outsourced'))

# 2012 USA population from https://www.multpl.com/united-states-population/table/by-year
pop2012 <- 314e6
our_landuse_long <-
  melt(our_landuse, variable.name = 'origin', value.name = 'total_footprint')
our_landuse_long[, per_capita_footprint := total_footprint / pop2012 * 1e6 ]
```

```r
# Sum up annual and permanent cropland. Rename pasture to grassland
our_landuse_long[, land_type := ifelse(land_type %in% c('annual','permanent'),
                                       'cropland', 'grassland')]
our_landuse_sums <- our_landuse_long[scenario_waste == 'baseline',
                                     .(per_capita_footprint = sum(per_capita_footprint)),
                                     by = .(scenario_diet, land_type, origin)]

# Add additional grand totals
total_outsourced <- our_landuse_sums[,
                                     .(per_capita_footprint = sum(per_capita_footprint)),
                                     by = .(scenario_diet, origin)]
total_outsourced[, land_type := 'total']
our_landuse_sums <- rbindlist(list(our_landuse_sums, total_outsourced), use.names = TRUE)
our_landuse_sums[, source := 'this study']
setnames(our_landuse_sums, old = 'scenario_diet', new = 'diet')
```

Next, we harmonize the Laroche et al. estimates with ours. First, we sum cropland used for food and cropland used for feed, which aren't differentiated in our final estimates.

```r
laroche_landuse[, origin := ifelse(`Land type` == 'total', 'total', 'outsourced')]
laroche_landuse[, land_type := map_chr(strsplit(`Land type`, ' '), 1)]
setnames(laroche_landuse,
         old = c('Diet','Per capita footprint'),
         new = c('diet', 'per_capita_footprint'))
laroche_landuse_sums <-
  laroche_landuse[,
                  .(per_capita_footprint = sum(per_capita_footprint)),
                  by = .(diet, land_type, origin)]
laroche_landuse_sums[, source := 'Laroche et al.']

comparison_dat <- rbind(our_landuse_sums, laroche_landuse_sums)
```

Next, we matched the names of diets across the two studies. Laroche et al. investigated some diets that we didn't consider, and used different names. We matched their `AAD` (Average American diet) with our `baseline` diet, and their `EAT` diet with our `planetaryhealth` diet. Those should be identical. Their `lacto-ovo vegetarian` diet should correspond closely with our `vegetarian` (USDA healthy vegetarian) diet, so we matched those up for comparison purposes.

```r
comparison_dat[diet == 'AAD', diet := 'baseline']
comparison_dat[diet == 'lacto-ovo vegetarian', diet := 'vegetarian']
comparison_dat[diet == 'EAT', diet := 'planetaryhealth']
```

Results

Figure S34. Total land footprints from the present study and Laroche et al. 2020

The figure below shows that our estimates are uniformly higher due to differing methodology and potentially different definitions of system boundaries. For example, our total land footprint in the baseline case is 39% higher than Laroche and colleagues' estimate. However, the relative differences between diets are similar between studies. Importantly, the total land footprint (including both domestic and outsourced) decreases relative to baseline for the vegetarian and Planetary Health diets, as do the outsourced total and outsourced grassland footprints. However, the outsourced cropland footprints increase relative to baseline, with the vegetarian diet increasing more than the Planetary Health diet. Note that the individual panels have different y-axis limits.

```
p <- ggplot(comparison_dat[diet %in% c('baseline','vegetarian','planetaryhealth') &
                           (origin == 'outsourced' | land_type == 'total')],
       aes(x = diet, y = per_capita_footprint, group = source, fill = source)) +
  geom_col(position = 'dodge') +
  facet_wrap(land_type ~ origin, scales = 'free_y') +
  scale_y_continuous(expand = expansion(mult = c(0, 0.02)),
                     name = 'Per capita land footprint (m2/cap/y)') +
  theme_bw() +
  theme(legend.position = 'bottom',
        strip.background = element_blank(),
        panel.grid = element_blank()) +
  scale_fill_manual(values = c(viridis::viridis(7, alpha = 0.7)[c(3,6)]))
```

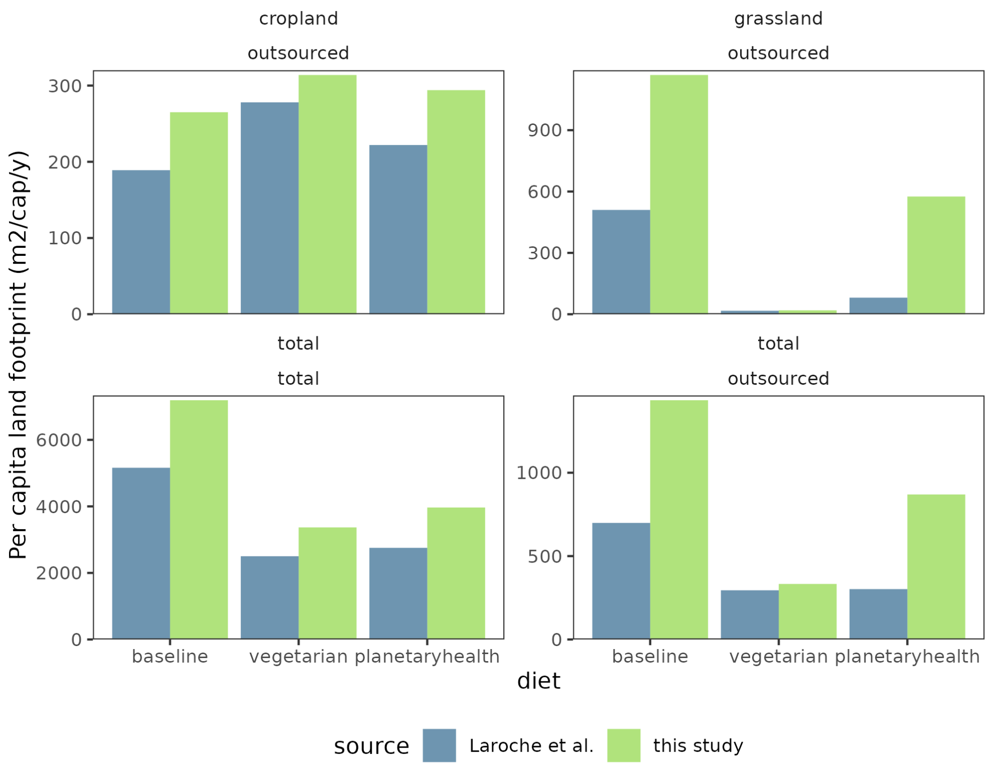

Figure S34: Comparison between our land footprint estimates and those of Laroche and colleagues

Table S10. Relative differences between our estimates and those of Laroche et al.

The *relative* column in the table below indicates the percent difference between the land footprint estimate of Laroche et al. and the corresponding estimate from the present study (differences between pairs of bars in the figure). For example a value of 129% indicates that our estimate is 129% higher, or 2.29 times as high, as the estimate from Laroche et al. All are positive indicating that our estimates are uniformly higher.

In particular, the pastureland (grassland) footprints for foreign imports are fairly different across the two studies, with our estimate over twice as high for the baseline case, and a full seven times higher for the Planetary Health diet. Thus, in general our study concludes that U.S. diets have a higher land footprint than the Laroche et al. (2020) study concludes, and that a higher share of it is imported. Relative to Laroche and colleagues, we found that less of a decline in land footprint would occur if an individual switched from the average American diet to the vegetarian or Planetary Health diets. Therefore Laroche and colleagues assume a greater reduction in environmental impact due to diet shifts than we do.

```
comparison_wide <-
  dcast(comparison_dat[diet %in% c('baseline','vegetarian','planetaryhealth')],
        diet + land_type + origin ~ source, value.var = 'per_capita_footprint')
comparison_wide[, relative := round((`this study`/`Laroche et al.` - 1), 2)]
```

Table S10. Relative differences between our estimates and those of Laroche and colleagues.

Diet	Land use type	Origin	Relative difference
baseline	cropland	total	—
baseline	cropland	outsourced	40%
baseline	grassland	total	—
baseline	grassland	outsourced	129%
baseline	total	total	39%
baseline	total	outsourced	105%
vegetarian	cropland	total	—
vegetarian	cropland	outsourced	13%
vegetarian	grassland	total	—
vegetarian	grassland	outsourced	12%
vegetarian	total	total	35%
vegetarian	total	outsourced	13%
planetaryhealth	cropland	total	—
planetaryhealth	cropland	outsourced	32%
planetaryhealth	grassland	total	—
planetaryhealth	grassland	outsourced	611%
planetaryhealth	total	total	44%
planetaryhealth	total	outsourced	188%

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