Mitigating risk of exceeding environmental limits requires ambitious food system interventions

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Abstract:

Transforming the global food system is necessary to avoid exceeding planetary boundaries. A robust evidence base is crucial to assess the scale and combination of interventions required for a sustainable transformation. We developed a risk assessment framework, underpinned by a meta-regression of 60 global food system modeling studies, to quantify the potential of individual and combined interventions to mitigate the risk of exceeding the boundaries for land-system change, freshwater use, climate change, and biogeochemical flows by 2050. Limiting the risk of exceedance across four key planetary boundaries requires a high but plausible level of ambition in all demand-side (diet, population, waste) and most supply-side interventions. Attaining the required level of ambition for all interventions relies on embracing synergistic actions across the food system.

Main Text:

The global food system is pushing several of the planetary boundaries that define the Earth's biophysically safe operating space into and beyond a zone of uncertainty (*1-4*), with potentially serious repercussions for the environment and human development (*5*). Business-as-usual (BAU) scenarios of global food production and consumption to 2050 are almost certain to exceed several planetary boundaries (*6-11*), and it is widely acknowledged that a transformation of the global food system is required to avoid transgressing these environmental limits. With attention focusing on interventions (pathways of action) that can limit the environmental impact of food systems (*12-15*), a comprehensive and integrated assessment of the scale and combination of interventions that can keep the Earth system within planetary boundaries is urgently required to support policy making and to catalyze necessary on-ground actions.

Over the past decade, global food system studies have presented a wealth of scenarios and estimates of the environmental benefits of a range of demand-side and supply-side interventions. However, the outputs and conclusions are sensitive to several analytical choices, including: modelling paradigm; input data and model parameterization; scenario specification; type and scale (or *ambition*) of interventions assessed; and the environmental indicators used (*16-18*). These choices are influenced by study aims and researcher worldview (*19, 20*), leading to bias and gaps in our understanding of the environmental impacts of food system trajectories and the effectiveness of interventions. Model intercomparisons of land-use change (*16, 18, 21, 22*) and narrative reviews of estimates for other indicators (*23, 24*) highlight the wide range in environmental impact estimates across studies. A systematic analysis of global food system modeling studies that can control for differences in methods and model assumptions, and synthesize the mitigation potential of a comprehensive suite of interventions is therefore needed.

The quantitative environmental limits that define planetary boundaries are often set conservatively to avoid exceeding biophysical tipping points (*1, 2, 25*) and include a zone of uncertainty that accounts for incomplete scientific knowledge and variability in Earth system functioning (*26*). The share of this safe operating space available to the food system is also uncertain and dependent upon assumptions about the environmental impacts of other sectors (*6, 7*). Given these uncertainties, a risk assessment framework can enhance the evaluation of food system interventions by determining the probability or *risk* of exceeding environmental limits.

Here, we present a quantitative synthesis of 60 global food system modeling studies. Our analysis is underpinned by a comprehensive database with thousands of unique projections to identify the synergies and trade-offs of various interventions, and the combinations that keep the food system within the Earth's safe operating space by 2050. We developed a quantitative risk assessment framework and a suite of statistical *meta-regression* models that estimate the risk mitigation potential of major food system interventions across four planetary boundaries (land-system change, freshwater use, climate change, and biogeochemical flows), controlling for a wide range of food system model sensitivities and uncertainties in environmental limits. Our analysis delivers comprehensive risk mitigation estimates of individual interventions and explores the intervention combinations and necessary on-ground actions that can keep the food system within planetary boundaries.

Intervention modelling and risk assessment

We systematically reviewed modeling studies of the global food system published since the year 2000, with environmental impact estimates up to and including 2050, and selected 60 journal articles and major international reports based on strict inclusion criteria from an initially identified 1419 studies [see SM (*27*) Section 1.1, Fig. S1]. We then assembled a comprehensive dataset (Data S1) of projected future food system impacts for 10 commonly used environmental indicators that adequately represent the four planetary boundaries assessed in this analysis (Fig. 1). The scope of our review encompasses terrestrial crop and livestock systems including inputs to aquaculture, but excludes environmental impacts associated with changes in demand for biofuels, non-food crops, and marine fisheries.

Food system modeling studies typically construct a BAU scenario that follows historical trends in food demand and agricultural productivity (*17*). Intervention scenarios range from marginal to substantial deviations from the BAU (*28*), based on a range of supply-side and demand-side actions that can reduce environmental impacts (Table S4). *Supply-side* interventions include improved farm management, increased efficiency, and technological advances that reduce resource use (*29, 30*) and emissions (*31*) (e.g., yield gap closure in crop and livestock systems, or more fundamental agronomic interventions such as changes in feed composition). *Demand-side* interventions assume socio-cultural changes such as reduced food waste and shifts towards plant-based diets (*32*) (Fig. 1A). Typically, studies either assess just a single intervention or storylines integrating multiple interventions such as the shared socioeconomic pathways (SSPs) (*18*, *22*). This makes it difficult to untangle the effect size of each intervention, and the intervention scale and combinations are limited to those encompassed in integrated storylines instead of spanning the entire range of possible futures (Table S7).

To enable a quantitative synthesis of food system interventions, identified 10 key environmental indicators representing four planetary boundaries (Table 1). We then selected and harmonized a set of quantitative variables representing major interventions (Table 2). We used the compiled data to fit linear mixed-effects meta-regression models for each of the environmental indicators, with intervention variables as predictors and the effect size (environmental impact relative to the base year) as the dependent variable [SM (*27*) Section 1.4]. We established four representative levels of mitigation ambition (Low, Trend or BAU, High, and Very High) for each intervention spanning a plausible range of ambition for 2050, based on the reviewed literature (Table 2). Using the meta-regression models, we simulated all plausible combinations of relevant intervention levels against each environmental indicator for 2050 (Fig. 1B).

We then defined food-system specific environmental limits as probability density functions (PDFs) capturing the best estimate and uncertainty zone for each planetary boundary (Table 1, Table S2). Following principles of probabilistic risk assessment (*33*), the risk of exceeding planetary boundaries for each meta-regression projection was calculated by comparing Gaussian distributions drawn from modeled prediction intervals against environmental limit PDFs (Fig. 1C, Fig. S2). Finally, we identified combinations of mitigation levels across interventions that ensure environmental risk across all boundaries remains below two critical risk thresholds compatible with the calibrated uncertainty language applied in IPCC assessments for describing quantified uncertainty (*34*, *35*): < 0.50 risk (exceedance *about as unlikely as not*) and < 0.33 risk (exceedance *unlikely*).

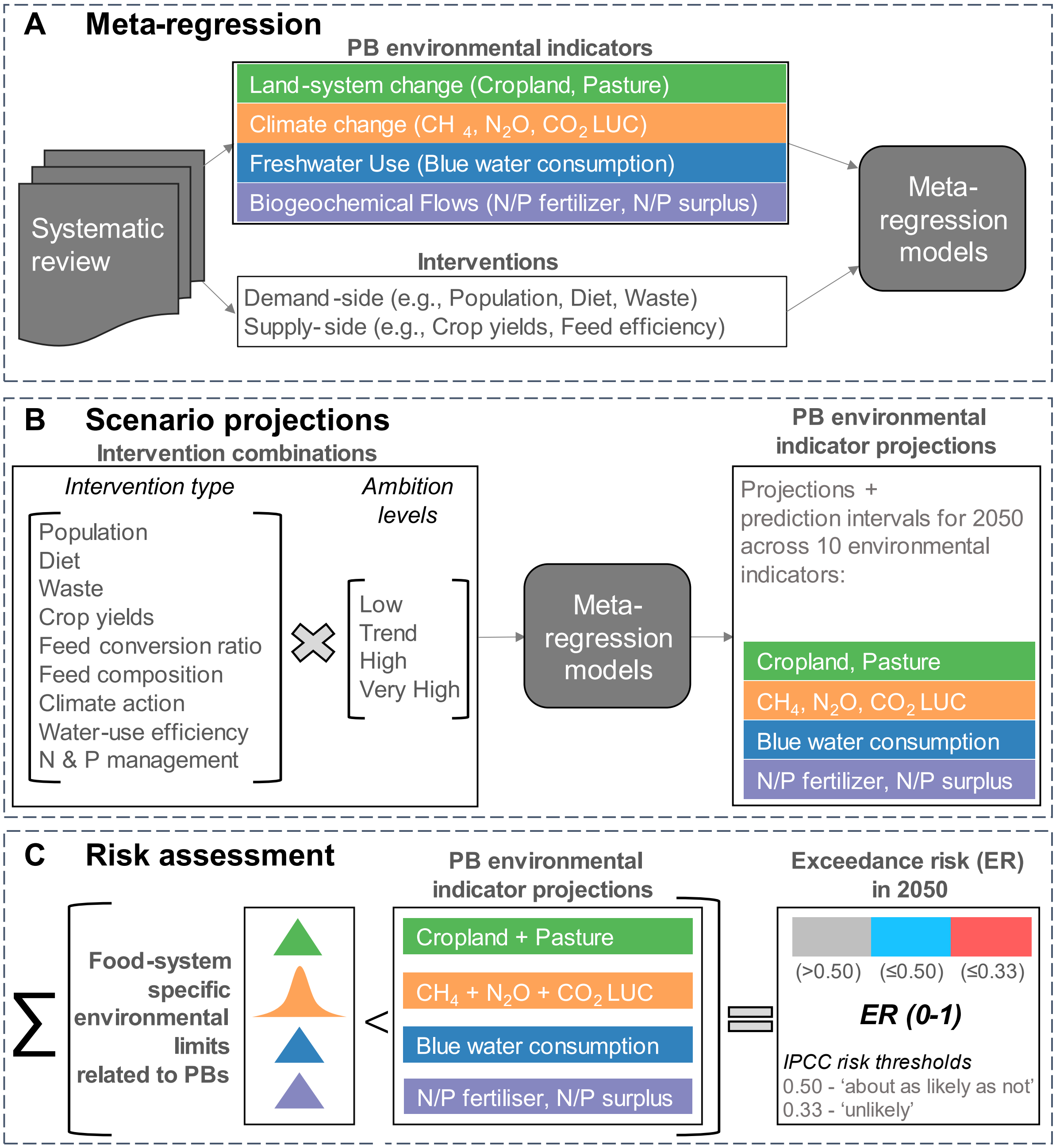


Fig. 1. Intervention modeling and risk assessment framework. A simplified illustration of the three main stages of analysis [see SM (*27*) Section 1 for details] **A.** Linear mixed effects meta-regression models fitted using planetary boundary (PB) environmental indicators corresponding to four key PBs (land-system change, climate change, freshwater use, biogeochemical flows), and intervention-related variables extracted from selected studies. **B.** Database with mean projections and prediction intervals for each of the 10 PB environmental indicators comprising

all relevant intervention combinations (Table 1). **C.** Exceedance risk calculation combining environmental limit probability density functions (Table 2, Table S2) and linear mixed model scenario projections. [PB = planetary boundary, LUC = land-use change, N = Nitrogen, P = Phosphorus].

Table 1. **Food-system specific environmental limits for selected environmental indicators in 2050.** Includes best estimate, lower bound, and upper bound [see SM (*27*) Section 1.2 for methodology and data sources]. In italics are the additive indicators used to assess overall risk across a planetary boundary (for full details see Table S3).

Planetary boundary (units)	**Indicator/*Boundary***	**Abbreviation**	**Environmental limit best estimate (low – high estimate)**	**Boundary description**
Land-system change (Mkm^2)	Total land area under crop production	Cropland		Total land area under agriculture (cropland + pasture) compatible with the 54-75% global forest cover requirement across major forest biomes (*2*).
	Total land area under permanent grassland	Pasture		
	Total agricultural area (i.e., cropland + pasture)	*TotalAgArea*	<33.1 (30.2 – 54.6)	
Climate change (Gt CO_2e yr^{-1})	Direct on-farm CH_4 emissions	CH_4		Total agriculture emissions (direct CH_4 + N_2O + net CO_2 emissions from land use and land-use change) in line with 67%/50% chance of remaining within 2.0/1.5 °C respectively (*36*).
	Direct on-farm N_2O emissions	N_2O		
	Land-use change CO_2 emissions	CO_2LUC		
	Direct on-farm non-CO_2 + net emissions from land-use and land-use change	*NonCO_2+LUC*	<3.53 (-3.52 – 10.6)	
Freshwater use (km^3 yr^{-1})	*Blue water (i.e., surface water + ground water) consumption by agriculture*	*Water*	<2270 (685 - 4040)	Total consumptive blue water use in agriculture adjusted for possible pathways in consumptive water use across other economic sectors, in relation to basin-level assessments of environmental flow requirements (*37*).
Biogeochemical flows - Nitrogen (Tg N yr^{-1})	Total nitrogen fertilizer application in agriculture	N_{fert}	<69 (52 - 130)	Individual boundaries for N_{fert}, $N_{surplus}$, P_{fert} and $P_{instream}$ based on latest consensus in global environmental limits (*2, 7, 38*). No cumulative boundary was possible due to the non-additive nature of the individual indicators. Instead, risk estimates were averaged across indicators to derive boundary risk metrics.
	Nitrogen surplus from agricultural land (i.e., N inputs minus outputs)	$N_{surplus}$	<90 (50 - 146)	
Biogeochemical flows – Phosphorus (Tg P yr^{-1})	Total phosphorus fertilizer application in agriculture	P_{fert}	<16.0 (6.2 – 17.0)	
	Phosphorus leaching from agricultural land (i.e., P inputs minus outputs)	$P_{instream}$	<2.89 (1.93 – 3.95)	

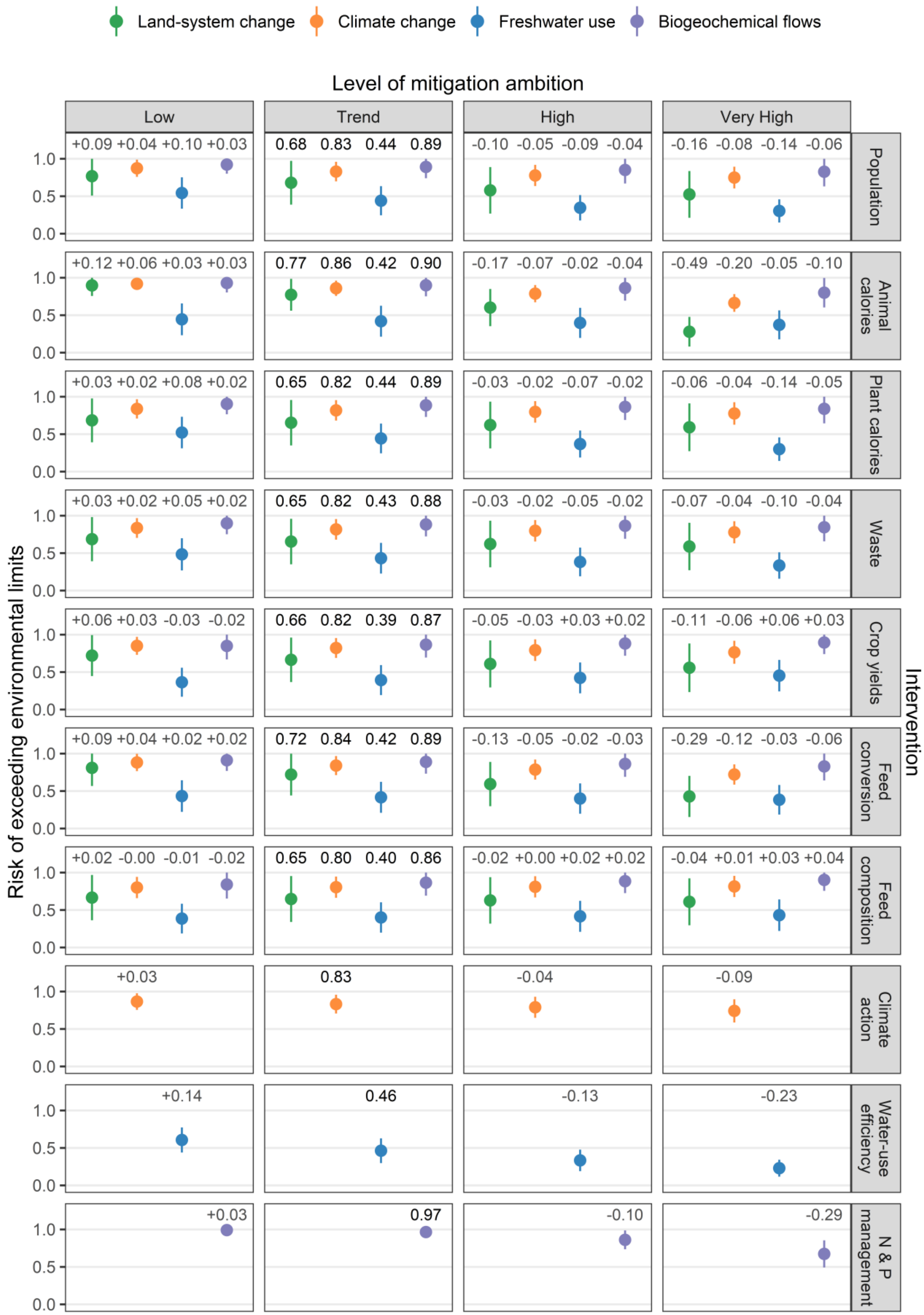
Table 2. Intervention levels and combinations analyzed in this study. Includes the levels of mitigation ambition across interventions used to project global food system performance against environmental indicators in 2050 and typical on-ground mitigation actions as synthesized from the 60 systematically selected studies [see (*27*) Table S4 & Data S4 for full study list and details]. Relevant boundaries include only those where a given intervention would be expected to be most influential. Not all interventions were fitted to all relevant indicator models due to multi-collinearity concerns or insufficient data [see SM (*27*) Section 1.4]. [ASF = animal-source foods, DM = dry matter, FCF = food-competing feed, EI = environmental intensity, NUE = nutrient-use efficiency].

Interventions	Level of mitigation ambition				Units	*Description*. Mitigation action example.	Relevant boundaries
	Low	Trend	High	Very High			
Demand-side							
Population	10.6	9.7	8.9	8.5	Billion people	*Global human population following the low, median and high projections in (39) and SSP1 (40).* This intervention could be enabled through reducing fertility rates via promoting education and reproductive health services (*41, 42*).	All
Diet						*Global daily average animal for ruminant meat, dairy, and monogastric products (pork, chicken, eggs and farmed seafood) and plant calorie intake per person (excluding waste).* Changes in diet could be enabled through promoting diet change towards plant-based diets and reduced overconsumption of animal and plant calories in high-income countries via market-based incentives, e.g. taxes, and/or awareness campaigns such as pro-environmental dietary guidelines (*43*). All combinations between animal and plant calories guarantee a minimum intake of 2145 kcal cap^{-1} day^{-1} that meets minimum dietary energy requirements for healthy populations with body mass index values between 18.5 and 24.9 (*7*) and meets the World Health Organization recommended vitamin B_{12} intake of 2.4 μg day^{-1} for adults and adolescents (*44*). Values >2400 kcal cap^{-1} day^{-1} could be	All
Animal calories	Rich	BAU	Low meat	Low ASF	kcal cap^{-1} day^{-1}		
Ruminant	65	50	40	25			
Dairy	170	150	160	115			
Monogastric	320	260	230	145			
Plant calories	2350	2185	2020	1860	kcal cap^{-1} day^{-1}		

Interventions		Level of mitigation ambition				Units	*Description*. Mitigation action example.	Relevant boundaries
		Low	Trend	High	Very High			
							considered representative of overconsumption in predominantly sedentary high-income populations (*45*) (see Table S8 & Table S9).	
Waste		25	0	-25	-50	%Δ	*Change in household and retail waste across all food categories (meat, dairy, seafood, cereals, pulses, fruit and vegetables) relative to 2010*. Reduction in household and service waste could be achieved through changes in the size or type of plates and education and awareness campaigns (*14*) (see Table S10).	All
Supply-side								
Crop yields		15	30	45	60	%Δ	*Global weighted yield increase per unit area for all crops relative to 2010.* Crop yields could be increased via breeding and genetic technologies, agronomic practices optimized to local climatic and soil conditions, and enhanced nutrient management (e.g., precision agriculture) (*46*).	All
Feed conversion ratio *Ruminant meat* *Dairy* *Monogastric*		 35 2 4	 30 1.75 3.5	 25 1.5 3.0	 20 1.25 2.5	kg DM / kg output	*Global weighted average animal feed conversion ratios (FCRs) for different livestock systems (ruminant meat, dairy and monogastrics).* Reductions in FCRs corresponding to increased feed efficiency can be achieved through developments in animal breeding and nutrition (*47*) (see Table S11).	All
Feed composition *Ruminant meat* *Dairy* *Monogastric*		 5 15 80	 10 20 85	 15 25 90	 20 30 95	% FCF	*Share of FCF (i.e., crops and fodder produced on land that could otherwise produce human food) in livestock feed by livestock type (ruminant meat, dairy and monogastrics)*. This two-way intervention can involve either increasing the amount of ecological leftovers (i.e., grass, food waste, by-products) used to feed livestock and the use of degraded/abandoned land for livestock production (*20*), or intensification of livestock production in feedlots (see Table S12).	All
Climate action (emissions intensity)	EI_{CH4}	0	13	26	40	%Δ	*Global reduction in non-CO_2 (CH_4 & N_2O) greenhouse gas (GHG) emissions intensity (emissions per unit of food produced) relative to 2010.* This can involve shifts toward agricultural practices that minimize emissions from soils and rice production, improved manure management, and feed supplements to reduce enteric fermentation in ruminants (*48*).	Climate change
	EI_{N2O}	0	4	8	12	%Δ		
	Carbon price	0	25	100	200	US\$2010 tCO_2eq^{-1}	*Carbon price effects on net CO_2 emissions from agricultural land use.* Relevant actions triggered by an increase in carbon price include avoided deforestation, regrowth and reforestation, and farming practices that promote soil carbon sequestration (*15, 31*).	
Water-use efficiency		0	10	20	30	%Δ	*Increase in the ratio of crop yield to the volume of water consumed (in kg of crop relative to blue water consumption in m^3) across all crops (including animal feed) relative to base year (2010) levels.* Increases can be achieved through crop breeding and selection, soil-water conservation practices that improve the productive capacity of soil, and precision irrigation techniques (*30, 49*).	Water
N & P management								Bio-geochemical flows
Nutrient-use efficiency	NUE_N	0	10	20	30	%Δ	*Increase in the amount of nitrogen (NUE_N) and phosphorus (NUE_P) uptake by crops as a proportion of the total amount of N and P fertilizer applied, respectively, relative to 2010.* Higher NUEs could be achieved through better nutrient management (e.g., optimizing fertilizer selection, timing, application) and regulation of application rates (*50*). For N the Very High setting corresponds to an increase from a global 2010 average NUE_N of 0.46 (*51*) to 0.60 by 2050. For P this corresponds to a change from 0.67 (*9, 38*) to 0.78 in 2050.	
	NUE_P	0	5	10	15	%Δ		
Nutrient recycling	P	0	15	30	45	%	*The proportion of phosphorus from human waste and excreta recycled and used as agricultural fertilizer relative to 2010.* This intervention requires improved infrastructure (pit latrines, septic tanks, enhanced sewage systems) to enable the recycling of nutrients from wastewater in agriculture (*38, 50*).	

Risk mitigation potential of individual food-system interventions

Based on simulations of all interventions at the four levels of mitigation ambition, we present the absolute risk of exceeding planetary boundaries for the Trend ambition level, and the effect size (*risk difference*, i.e., risk mitigation potential relative to the Trend) for all other intervention levels in 2050 (Fig. 2; Fig. S4 & Fig. S5). To illustrate the results in the sections below, we use individual interventions set at the Very High level of mitigation ambition to show the maximum risk mitigation potential (expressed as risk difference and reduced pressure in physical units), and discuss potential synergies and trade-offs.



Land-system change
Climate change
Freshwater use
Biogeochemical flows
Level of mitigation ambition
Low
Trend
High
Very High
Risk of exceeding environmental limits
Intervention
Population
+0.09 +0.04 +0.10 +0.03
0.68 0.83 0.44 0.89
-0.10 -0.05 -0.09 -0.04
-0.16 -0.08 -0.14 -0.06
Animal calories
+0.12 +0.06 +0.03 +0.03
0.77 0.86 0.42 0.90
-0.17 -0.07 -0.02 -0.04
-0.49 -0.20 -0.05 -0.10
Plant calories
+0.03 +0.02 +0.08 +0.02
0.65 0.82 0.44 0.89
-0.03 -0.02 -0.07 -0.02
-0.06 -0.04 -0.14 -0.05
Waste
+0.03 +0.02 +0.05 +0.02
0.65 0.82 0.43 0.88
-0.03 -0.02 -0.05 -0.02
-0.07 -0.04 -0.10 -0.04
Crop yields
+0.06 +0.03 -0.03 -0.02
0.66 0.82 0.39 0.87
-0.05 -0.03 +0.03 +0.02
-0.11 -0.06 +0.06 +0.03
Feed conversion
+0.09 +0.04 +0.02 +0.02
0.72 0.84 0.42 0.89
-0.13 -0.05 -0.02 -0.03
-0.29 -0.12 -0.03 -0.06
Feed composition
+0.02 -0.00 -0.01 -0.02
0.65 0.80 0.40 0.86
-0.02 +0.00 +0.02 +0.02
-0.04 +0.01 +0.03 +0.04
Climate action
+0.03
0.83
-0.04
-0.09
Water-use efficiency
+0.14
0.46
-0.13
-0.23
N & P management
+0.03
0.97
-0.10
-0.29
1.0
0.5
0.0

Fig. 2. Modeled risk of exceeding environmental limits in 2050 for four planetary boundaries under a range of ambition levels for selected interventions. Each panel presents average risk estimates for a specific level of mitigation ambition (facet columns) of a selected intervention (facet rows), as per Table 1 across land-system change ($n = 4^7 = 16,384$), climate change ($n = 4^8 = 65,536$), freshwater use ($n = 4^8 = 65,536$), and biogeochemical flows ($n = 4^8*2 = 131,072$). Data are presented as mean values (bubbles) +/- one standard deviation (SD) (vertical lines). Risk estimates encompass both model uncertainty and uncertainty in environmental limits [see (*27*), Section 1.4; Figure S4 & S5 for estimates in physical units for each indicator; Data S5 for full dataset]. Black numbers at the top of panels indicate absolute mean exceedance risk (0-1) for the Trend (BAU) level, where a score of 1 represents 100% probability of a planetary boundary being exceeded by 2050. Grey numbers indicate mean risk difference relative to the Trend for all other levels. Missing bars correspond to interventions excluded from individual models due to lack of relevance, adverse impacts on model performance, collinearity, or missing/insufficient data.

Synergies across planetary boundaries

Demand-side interventions show high risk reduction potential across all indicators, with some variability across boundaries (Fig. 2). Shifting to diets with a low proportion of animal-source food (ASF) (Very High ambition) could achieve the maximum risk reduction across land-system change (-0.49; -1363 Mha) and climate change (-0.20; -3.07 $GtCO_2eq$), reflecting substantially reduced demand for pasture and feed crops and reduced enteric fermentation (Fig. S4). A low ASF diet also shows considerable risk mitigation potential in relation to freshwater use (-0.05; -107 km^3), and biogeochemical flows (-0.10; -14.8 Tg N_{fert}, -2.11 Tg P_{fert}). Other demand-side interventions also result in strong risk reduction potential across boundaries, especially for land-system change (up to -0.16; -539 Mha for population interventions), climate change (-0.08; -1.38 $GtCO_2eq$ for population interventions), and freshwater use (-0.14; -307 km^3 for plant calorie interventions) (Fig. 2; Fig. S4, Fig. S5).

Among supply-side interventions, improvements to feed conversion ratios have the highest overall mitigation potential across planetary boundaries, with a strong effect on land-system change (-0.29; -939 Mha) and climate change (-0.12; -2.02 $GtCO_2eq$) – owing to significantly reduced feed demand from both cropland and pasture (Fig. 2; Fig. S4). Targeted interventions such as water-use efficiency and N/P management show the highest overall potential for reducing the risk of exceeding the freshwater use boundary, and N and P boundaries, respectively (Fig. S5). Unlike climate change and land-system change, exceedance risk for freshwater use and biogeochemical flows associated with irrigation and fertilizers responds more strongly to targeted supply-side interventions than to demand-side interventions.

Trade-offs between planetary boundaries

Unlike other interventions, actions to increase crop yields and change feed composition exhibit trade-offs (Fig. 2). Higher (+60%, Very High ambition) crop yields result in a significant reduction in exceedance risk for land-system change (-0.11; -357 Mha) and associated GHG emissions (-0.06; -0.92 $GtCO_2eq$), because of avoided cropland expansion and forest regrowth substantially outweighing the increase in nitrous oxide emissions from additional fertilization (Fig. S4). However, higher crop yields could increase the overall risk of exceedance for freshwater use (+0.06; +131 km^3) and biogeochemical flows (+0.03; +3.65 Tg N_{fert}, 0.80 Tg P_{fert}) (Fig. 2; Fig. S4). In the absence of any concomitant feed conversion improvements, a higher grain percentage in livestock feed still reduces overall risk for land-system change (-0.04; -131 Mha), as pasture reduction (-280 Mha) more than offsets cropland increase (+149 Mha) (Fig. S4). However, this could entail increased risk for freshwater use (+0.03; +67 km^3) and biogeochemical flows (+0.04; +17.5 Tg N_{fert}, +1.38 Tg P_{fert}) from additional inputs, along with a small increase in climate change risk (+0.01; +0.22 $GtCO_2eq$) due to emissions from cropland expansion and additional fertilization offsetting any negative emissions from pasture abandonment (Fig. 2; Fig. S4, Fig. S5).

Intervention combinations to achieve risk mitigation thresholds

No single intervention achieves substantial risk mitigation (risk mitigation > 0.1) across all boundaries. To effectively reduce risk across all environmental indicators, a comprehensive portfolio of demand-side and supply-side interventions is required. Recent work has focused on a limited combination of highly ambitious best-case interventions, raising concerns around feasibility (*13, 52*). Here, we mapped the performance of all intervention combinations against their risk mitigation and ambition level. We did this individually for each of the four planetary boundaries and together for all boundaries, encompassing the full set of 2,090,238 plausible combinations of intervention levels for each individual indicator across all boundaries (Table S14). We then selected the combinations that met two critical IPCC calibrated uncertainty risk thresholds (*35*) across all boundaries: < 0.50 risk (exceedance *about as unlikely as not*) and < 0.33 risk (exceedance *unlikely*).

Only 0.51% of all combinations achieve a risk <0.50 for all boundaries, with an even smaller subset of 0.01% combinations achieving the risk <0.33 (<0.4 for climate change) threshold (Fig. 3A). This reflects the interplay of synergies, trade-offs, and dependencies arising from different interventions and ambition levels. While considerably more combinations show low levels of risk at the global level for land-system change and freshwater use, the safe operating space is considerably more restricted for biogeochemical flows and climate change (Fig. 3A; Fig. S6).

Visualizing the combinations that meet each risk threshold highlights the required ambition levels for each intervention (Fig. 3). Despite significant differences between risk < 0.50 and risk < 0.33 thresholds, over 91% of all compliant combinations in both cases require Very High ambition for animal calories and N and P management (Fig. 3B). A predominantly High-Very High ambition across animal and plant calories is critical in both risk < 0.50 and risk < 0.33 compliant combinations (Fig. 3B). In contrast, for population and waste, risk < 0.50 compliant combinations had small percentages of Low or Trend ambition. However, for risk < 0.33 compliant combinations, more than 68% of compliant combinations require Very High ambition across demand-side interventions, with this percentage rising to 79% for population and plant calories, and 100% for animal calories (Fig. 3A). High-Very High ambition levels are required for N and P management, feed conversion ratios and climate action across more than 90% of all risk < 0.50 combinations, while over 83% of risk < 0.33 combinations require Very High ambition across these interventions.

Other supply-side interventions (crop yields, feed composition and water-use efficiency) have a greater range of ambition levels that achieve risk thresholds (Fig. 3A). Increases in crop yields are critical for maintaining a low risk of exceedance for land-system change and climate change, with 75% and 92% of risk < 0.50 and risk < 0.33 combinations requiring High-Very High levels of ambition. Nevertheless, potential trade-offs of higher yields for freshwater use and biogeochemical flows (Fig. 2) mean that less than around half of all compliant combinations require Very High levels of ambition. For feed composition, Low-Trend ambition, indicative of livestock systems that use more grass or by-products (see Table 2), is required across 58% of risk < 0.50 and 69% of risk < 0.33 combinations. Maintaining a high percentage of non food-competing feed (*53*) is preferable in combinations with a High-Very High level of ambition for animal calories, avoiding trade-offs associated with feed intensification (Fig. 2). For water-use efficiency, only around half of all risk-compliant combinations have High-Very High ambition levels (Fig. 3A), reflecting the generally safer status of the global freshwater use boundary and the high water use mitigation potential of Very High ambition levels across demand-side interventions (Fig. 2) within combination sets.

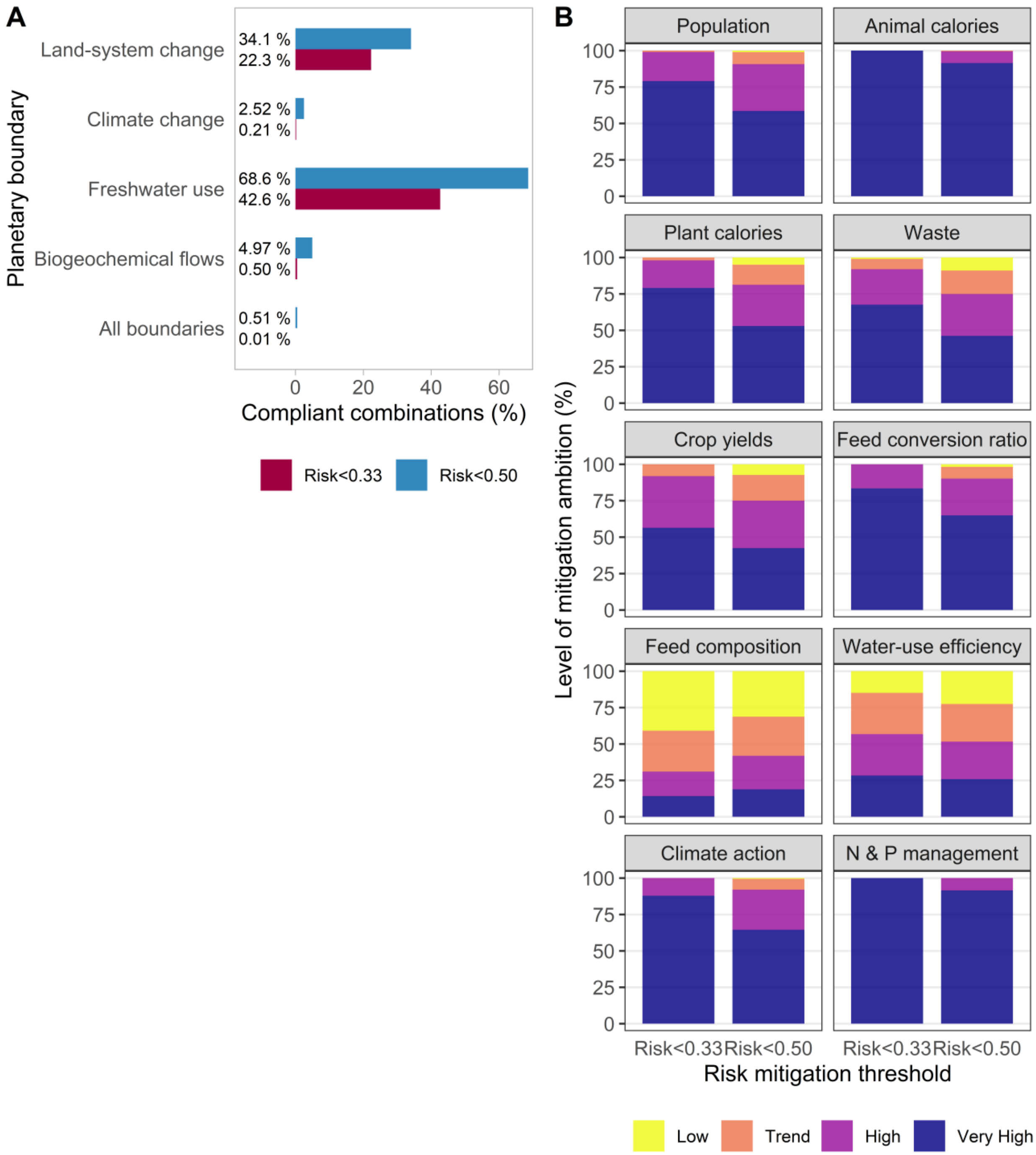


Fig. 3. Percentages of risk-compliant combinations and required intervention ambition levels to meet alternative risk thresholds. A. The horizontal bar plot displays the percentages of combinations that meet each of the two risk thresholds (risk < 0.50 and risk < 0.33) for each boundary and combined for all boundaries. **B.** The

vertical bar plots display the percentages of each of the four levels (Low, Trend, High, Very High) of mitigation ambition for all intervention combinations that meet each of the two risk thresholds across all boundaries.

Actions to enable risk-compliant intervention combinations

While substantial risk reduction for individual indicators is possible even with marginal increases in mitigation ambition relative to expected trends (Fig. S6), ensuring unlikely exceedance (<0.33) across all four planetary boundaries in 2050 requires at least a High level of ambition across all demand-side interventions in addition to most supply-side interventions. Certain interventions such as diet (animal calories) and N/P management require a Very High level of ambition. Despite the narrow option space of interventions that would allow the Earth system to remain within planetary boundaries, and significant feasibility challenges, such ambitious mitigation levels remain within reach – provided the numerous and diverse opportunities for action across the food system (Table 3, Data S3) are fully exploited.

Table 3. Mitigation actions discussed in reviewed studies mapped to relevant interventions. The table provides a non-exhaustive list of actions with selected examples across the food system, as qualitatively mentioned in the 60 systematically selected studies (for further detail see Data S3). Grey cells indicate that an action has the potential to contribute to an intervention but are not intended to be indicative of the strength of association between actions and interventions. Blank cells indicate a low potential association or no relationship between an action and an intervention. Supply-chain scope (i.e., farm-level, processing and retail, consumers, agricultural policy, research and development) follows the categories used in (*54*). Actions are listed alphabetically within each scope category.

		Interventions									
		Demand-side			Supply-side						
Scope	Action categories (examples)	Population	Diet	Waste (inc. loss)	Crop yields	Feed conversion	Feed composition	Climate action	Water-use efficiency	Nutrient-use efficiency	Nutrient recycling
Farm-level	Advanced agronomic technologies (e.g., precision farming)				■			■	■	■	
	Advanced crop production techniques (e.g., hydroponics)				■			■	■	■	
	Agronomic conservation practices (e.g., minimum/no till)				■			■	■	■	■
	Biochar addition to soil							■			
	Bioenergy crop cultivation on degraded or abandoned land							■			
	Enhanced nutrient management strategies				■			■		■	■
	Fine-tuning feed composition to improve digestibility					■	■	■		■	
	Genetic modification (e.g., higher-yielding crops/animals)				■	■		■	■	■	
	Globally optimised cropland use (shifting to efficient areas)				■						
	Improved agronomic management (e.g., timing of sowing)				■			■	■	■	
	Improved irrigation efficiency (e.g., drip irrigation)								■		
	Improved sewage systems (e.g., separate urine collection)										■
	Improved water management techniques				■				■		
	Increased fertiliser use in under-yielding countries				■			■		■	
	Integration of biogas plants and manure storages							■			■
	Livestock herd management (e.g., short rotation grazing)					■	■	■		■	■
	Locally appropriate crops (e.g., climate-resilient cultivars)				■				■	■	
	Nitrification and urease inhibitors							■		■	
	Nutrient recovery (e.g., use of crop residuals and manure)				■		■	■		■	■
	Reduction in crop feed (e.g., use of grass and by-products)					■	■	■		■	
	Shifting livestock production to dairy/monogastrics					■	■	■			
	Slow-release fertilizers and fertigation									■	
	Transition towards fodder-based livestock production					■	■	■			
	Veterinary health measures for livestock (e.g., vaccination)					■		■		■	
Processing & Retail	Circular supply chain designs to recycle food waste			■							■
	Digital infrastructure (e.g., internet and GSM coverage)			■							
	Food preservation practices that reduce spoilage			■							
	Improved cold-chain infrastructure			■							
	Improved inventory management and purchasing			■							
	Improved packaging for extended shelf life			■							
	Improved transportation, processing, and storage facilities			■							
	Recovery and redistribution of surplus food (e.g., in retail)			■							

Scope	Action categories (examples)	Interventions: Demand-side: Population	Diet	Waste (inc. loss)	Supply-side: Crop yields	Feed conversion	Feed composition	Climate action	Water-use efficiency	Nutrient-use efficiency	Nutrient recycling
Consumers	Dietary guidelines for healthy and sustainable diets		■	■							
Consumers	Education and awareness campaigns		■	■							
Consumers	Family planning (e.g., education and empowerment)	■	■								
Consumers	Food labeling regulations with sustainability scoring		■	■							
Consumers	Government regulation (e.g., consumption mandates)		■								
Consumers	Integrating sustainability in social protection programmes		■	■							
Consumers	Market-based instruments (e.g., carbon price, health tax)		■	■	■	■	■	■	■	■	■
Consumers	Novel protein sources (e.g., algae, mycoprotein, insects)		■								
Consumers	Nudges towards plant-based diets (e.g., rewards schemes)		■	■							
Consumers	Nutrition counselling in maternal/childcare programmes		■								
Consumers	Promotion of more sustainable diets in gastronomy		■	■							
Consumers	Public procurement (e.g., meals in schools and hospitality)		■	■							
Consumers	Transforming food environments (e.g., sustainable snacks)		■								
Agricultural policy	Access to affordable credit (e.g., co-operative banks)				■	■		■	■	■	
Agricultural policy	Climate policies strongly linked to agricultural strategies		■			■	■	■		■	
Agricultural policy	Enabling farmers to make long-term investments			■	■	■	■	■	■	■	■
Agricultural policy	Enhanced market access (e.g., better rural infrastructure)			■	■						
Agricultural policy	Establishment of productivity standards and targets			■	■	■	■	■	■	■	■
Agricultural policy	Improved access to pollination services				■						
Agricultural policy	Policies to regulate agricultural runoff									■	
Agricultural policy	Specialization to optimize trade and resource allocation				■	■		■	■	■	
Agricultural policy	Payment for ecosystem services							■			
Agricultural policy	Strict regulation and restrictions on resource use								■	■	■
Agricultural policy	Trade liberalization (i.e., reforming tariffs and subsidies)			■	■	■	■	■	■	■	
R&D	Increased investment in research, technology, innovation		■	■	■	■	■	■	■	■	■
R&D	International working groups on sustainable consumption		■	■							
R&D	Technical assistance and capacity building		■	■	■	■	■	■	■	■	■
R&D	Technology and knowledge transfer		■	■	■	■	■	■	■	■	■

Achieving the required demand-side intervention levels

A major barrier to achieving the required levels of demand-side mitigation is the feasibility of implementing transformative global-scale actions within the available timeframe (*12*, *48*). The required levels of mitigation by 2050 across diets, waste, and population are at odds with current patterns in high-income countries (*55*), the continued growth of the global middle class with associated increases in ASF (*41*), and trends in food waste (*56*, *57*) and population (*41*, *58*). However, increasing social awareness of the environmental mitigation potential of demand-side actions and their significant co-benefits with health and well-being (*43*, *59*), coupled with emerging options (*12*) to overcome systemic financial and political challenges (*48*), could, under the right policy settings, counter current trends. While demand-side actions tend to focus on consumer behavior, the broader economic and regulatory environment (Table 3) will need to evolve substantially to enable technological innovation and the changes in choice infrastructure necessary for shifting consumer behavior.

The adoption of low ASF diets with a significantly reduced ruminant meat intake (*14*), is critical. The pace of the ongoing nutrition transition (*55*) demonstrates that equally rapid and widespread shifts towards healthier, plant-based diets could also be achievable given the right policy settings (*60*). Studies tend to concentrate on consumer-centered actions such as incorporating sustainability into dietary guidelines and food labels, education and awareness campaigns such as public information programs on sustainable diets, investment in healthier food environments, and economic incentives such as health taxes (Table 3). Promoting shifts towards more legumes, nuts, and seeds in high-income countries represents a readily available option to reduce environmental risk while improving health outcomes (*14*). Novel protein alternatives (e.g., plant-based or lab-grown substitutes, mycoprotein, and insects) could catalyze dietary shifts, potentially offering additional environmental and health co-benefits (*61*), although their performance across certain micronutrients and their broader social and economic implications remain uncertain (*62*). More equitable income distribution could further facilitate dietary transitions (*43*). Actions tailored to specific country contexts, underpinned by concerted global efforts such as the UN Food Systems Summit (*63*), can promote sustained changes to overcome behavioral feasibility challenges (e.g., strong social norms and taste preferences favoring meat consumption) (*13*). Models with an endogenous social acceptability component suggest that the low ASF diet is achievable by 2050 (*64, 65*).

Highly complementary actions could achieve the necessary reduction in plant calories to address overconsumption and food waste. Many people in upper- and middle-income countries overconsume food due to lifestyles that lead to overweight and obesity (*48, 55*). Changes in sociocultural norms around plant-based diets can concurrently target a reduction of excess plant calories (particularly from highly processed carbohydrates and vegetable oils) and waste (*66*). A recent review highlights the effectiveness of interventions such as reductions in the size and type of servings in hospitality settings, changing nutritional guidelines in schools, and information campaigns (*67*). Additional actions include practices to reduce or reuse waste in food retail, such as improved packaging to extend product shelf life or more advanced inventory management (Table 3). More reliable and consistent food waste data is also of critical importance in informing national food waste strategies aspiring to an ambitious 50% reduction target, with some progress already underway in this respect (*57*). The significance of slowing population growth is often downplayed in food system studies (*41, 58*). Relevant actions that could ensure a maximum global population of 8.9 billion in 2050 include improved education to change social norms around family planning and family-size preferences, and empowering girls and women (*42*). Such measures could greatly reinforce efforts to change diets by tackling the combined negative effects of population growth and the nutrition transition (*41, 55*). More equitable redistribution of wealth through policies addressing inequalities in income and gender, and stronger linkages between climate, health, and agriculture policy portfolios, could also aid in providing the conditions for achieving the level of mitigation ambition required across all demand-side interventions (Table 3).

Achieving the required supply-side intervention levels

Equally ambitious actions are needed to achieve the required levels of supply-side mitigation. While the portfolio of proposed actions relies on technologies and management practices that increase the efficiency of food production at the farm scale, the broader policy, regulation, and research and development (R&D) context plays a crucial role in accelerating innovation and knowledge transfer across different geographic regions (Table 3).

Large feed efficiency gaps currently exist across different livestock production systems (*47*). Key actions to enable global feed conversion ratios to converge to those in developed countries include better animal breeding and husbandry, improving the digestibility of feed through changes in feed composition and supplements, and optimizing grazing management (Table 3). The overall protein conversion efficiency of the system also depends on demand trends. Both aquaculture (*68*) and plant-based proteins (*61*) are more efficient at producing food protein compared to most terrestrial livestock. A number of other options such as microbial protein feed

(*69*) and novel protein alternatives could further increase the overall efficiency of the food system while providing healthy protein.

Some actions that reduce feed conversion ratios (e.g., transitioning to grain-based livestock production) assume higher percentages of food-competing feed (FCF) (Table 3). The low ambition level in feed composition levels favors lower-FCF livestock systems that rely on crop by-products, food waste and pasture (*70*), and implement circularity (*70*) and agro-ecological (*19, 53*) principles of grazing and herd management (Table 3). However, low-FCF livestock systems can only provide a limited amount of animal protein due to their high pasture intensity (*71*), and are therefore contingent upon a low ASF diet. While high feed efficiencies in low-FCF livestock systems can be challenging (*70*), low-FCF grazing systems in Australia and New Zealand already achieve high efficiencies (*47*). Further actions such as sourcing meat from dairy herds (*20, 54*), novel feeds (e.g., microbial protein, insects), and livestock production in areas with higher pasture productivity (Table 3), could enable high-efficiency low-FCF livestock production at the global scale – provided diets remain low in ASF.

Actions that optimize livestock productivity (e.g., feed supplements) can also reduce methane emissions from enteric fermentation (*72*). Additional mitigation actions (*15, 48, 73*) can further reduce non-CO_2 emissions associated with crops and livestock. These include improvements in housing systems, manure storage, composting, and anaerobic digestion to reduce emissions from manure; and improved nutrient and residue management to reduce emissions from cropland soils and rice paddies (Table 3). A global carbon price provides an established mechanism to incentivize such actions with an additional positive effect on net CO_2 emissions from land use by reducing land clearing and promoting sequestration through trees and soil enhancement (*73*). While a carbon price of US$200 tCO_2eq^{-1} is higher than the US$100 tCO_2eq^{-1} currently considered cost-effective (*15*), it is still considered feasible for 2050, with considerable technical mitigation potential across all greenhouse gases – especially in developing regions like Latin America and Africa (*72, 73*).

Crop yields need to increase by 30-60% by 2050 relative to 2010. While a 30% increase follows historical (1970-2010) trends for cereal crops (*46*), this will still necessitate a number of on-farm actions, underpinned by higher investment and technology transfer (Table 3). These include continued improvements in management practices, advanced agronomic (e.g., precision farming) and genetic (e.g., higher-yielding and climate-resilient) technologies, and increased fertilizer availability and application in areas with significant yield gaps (*14, 48*). The anticipated impacts of climate change may pose challenges in certain major crop-growing regions (*74*). Furthermore, the assumed ambition levels are based solely on closing potential yield gaps in cereal crops, and do not reflect the challenges in achieving similar yield gains for non-cereal crops or for pasture. Trade-offs associated with higher yields (i.e., higher input requirements), can be reduced through synergistic actions that improve water-use efficiency (WUE) and N & P management (NUE and recycling) (Table 3).

For WUE, a 10-30% increase would necessitate similar investment and advancement in crop production techniques and technologies to those required to increase crop yields, with additional focus on soil-water conservation practices and improved water management techniques (e.g., rainwater harvesting, increased reliance on rainfed agriculture and deficit irrigation) (Table 3). The assumed WUE increase would require considerable investment but remains feasible given the plethora of actions available across different geographic contexts (*8, 30*). However, translating gains in WUE to actual water savings will also require more robust water accounting, stricter enforcement of caps to prevent water misuse and misallocation, and a better understanding of the socioeconomic context including behavioral responses of irrigators to increased WUE (*49*).

Attaining the required levels of N & P management requires enhanced nutrient management in croplands, pasture, and all animal agriculture (Table 3). Improved placement and timing of fertilizers, precision irrigation, integrated weed, pest, and disease management, enhanced manure storage and spreading methods, and more effective recycling of animal manures, can all increase NUE (*50*). Soil conservation practices (e.g., cover crops, tillage management, buffer strips) adapted to local conditions can further enhance NUE by minimizing erosion and subsequent nutrient runoff (*38*). Shifts to more plant-based diets can also increase the overall nutrient efficiency of the system, as intensive livestock production results in inefficiencies in nutrient use through feed demand and the crop mix required (*50*). P recovery from wastewater is currently more established and efficient (*75*), with less potential for reducing N fertilizer through wastewater recycling (*76*). However, up to ~35% of inorganic N from chemical fertilizer could in theory be offset by recycling all nutrients from food waste and wastewater in agriculture (*9*).

Multi-indicator target setting and risk assessment of food systems: challenges and future directions

Target-setting, such as the proposed 'net zero' equivalent target for the food system (*77*), could provide additional impetus towards transformative actions. However, ambitious targets are also necessary for other environmental indicators (*4*, *78*), and should also include an extended target space encompassing broader Sustainable Development Goal indicators – especially those intrinsically linked to the food system such as food and nutrition security, and livelihoods (*79*, *80*). While some mitigation actions are likely to show considerable co-benefits, others, especially those entailing high R&D investment, or if poorly implemented, could entail significant costs being passed on to producers with potentially adverse impacts on food prices and food security (*15*, *48*). Moreover, although our risk assessment focuses on boundary-level risk metrics, indicator-level results show that certain interventions create trade-offs within boundaries (e.g., between cropland and pasture or between greenhouse gases). Indicator-specific targets including shorter-term goals and associated risk metrics are therefore also required. For example, the 45% methane reduction target by 2030 recommended in UNEP's Global Methane Assessment (*81*) reflects methane's role as a short-lived but potent climate pollutant. Similar interim targets for specific indicators are necessary to inform interventions and enable actions. Risk assessment frameworks such as the one developed here can then be used to synthesize available evidence from multiple sources using a unified, quantifiable, and actionable metric (expressed in risk terms) to identify optimal intervention portfolios.

Interactions across Earth system processes are complex and often amplifying, and safeguarding *all* planetary boundaries is therefore essential (*1*, *2*). The presence of regional risk thresholds, as in the cases of land-system change and biosphere integrity (*11*), biogeochemical flows (*82*), and freshwater use (*8*), highlight the importance of setting environmental limits and targets at different levels, from global to sub-national. Ongoing refinements to the planetary boundaries framework, such as the inclusion of green water to the freshwater use boundary (*83*), and boundary interactions between climate change and other boundaries (*5*, *84*), point to increased risks across the Earth system. Our global risk estimates are partial as we do not encompass all planetary boundaries or potential interactions (*5*, *84*), and do not explicitly account for regional or seasonal exceedances (*8*, *76*). For this reason, additional interventions that achieve spatially optimized outcomes (*85, 86*) may be required to maximize the chances of respecting both global and local environmental limits.

Despite efforts to consider plausible intervention levels as consistent with the range in the published literature, as is the case for most food system scenario studies, our risk assessment framework does not explicitly consider or quantify feasibility challenges (*12, 13*). Food system sustainability frameworks must incorporate feasibility evaluation (*13, 87*) to allow a comparison of alternative intervention levels based on technological, economic, socio-cultural, and institutional barriers to identify optimum action pathways. Furthermore, while risk estimates capture the spread in responses across underlying models, statistical meta-regression does not capture how different underlying actions could influence effect size. For example, crop yields could increase because of total factor productivity (*42*), but could also increase through additional irrigation and fertilization inputs. Specific actions and mechanisms of implementation can make a material difference to any synergies or trade-offs across indicators and may also entail divergent implementation challenges (*12*).

Our analysis focuses on projections for 2050. Despite the large number of scenarios to ensure comprehensive coverage of the option space, we assume partial or full implementation of interventions without accounting for alternative implementation pathways in the period leading up to 2050. Our statistical models implicitly draw on the diverse pathways and intervention trajectories assumed in the underlying studies. Recent work (*6*) underlines the importance of the timing and pace of implementation, especially for climate change where the remaining carbon budget also depends on decarbonization trajectories in other key sectors such as energy and transport (*73*, *88*). Studies using dynamic process-based models consider non-linearities and saturation effects in intervention effectiveness associated with trends in technology and consumer behavior (*43*, *64*, *89*), as well as effects associated with regional heterogeneity in key food demand drivers such as population, income and agricultural research and development and their interactions with food prices (*90*). Future syntheses of intervention performance could compare non-linearities in implementation (rather than simply control for them as we have) using timeseries multi-model ensembles based on diverse pathways and narratives. Improved data sharing and harmonization of scenario indicator results and food system intervention parameters across studies, in a similar fashion to what is currently being practiced for IPCC climate mitigation scenarios (*36, 73*), would greatly facilitate future syntheses.

While we consider many possible futures, there are potentially more intervention combinations than those identified that meet risk thresholds. This includes values in between or beyond the four levels of ambition considered across each intervention, as well as additional interventions not explicitly considered in our analysis. For example, the emergence of innovation breakthroughs such as novel protein alternatives or other future technologies (*12*) could potentially expand the option space, with global food system models only just starting to explicitly incorporate them (*20, 89*). Future research efforts could more comprehensively consider the risk mitigation potential of available interventions and the numerous actions available to enable them across different contexts. Nonetheless, our work provides the most comprehensive synthesis and risk assessment to date on the mitigation potential of plausible food system intervention combinations for 2050, and clearly indicates the urgency of ambitious levels of action on both the demand and supply side of global food systems to give humanity the best chance of remaining within planetary boundaries.

Materials and Methods

Systematic review and data collection

We carried out a systematic literature search for scenario modeling studies of global food system sustainability following the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) protocol (*91*). We developed a universal search string refined using an article test list of 20 highly cited articles. We then used this string to search across four major academic databases (ProQuest, Scopus, Web of Science, Science Direct) to identify published journal articles and book chapters that contained quantitative scenario projections of global environmental impacts explicitly associated with food production for the year 2050 (Table S1, Fig. S1). We also searched for key reports from major food-related organizations (FAO, World Bank, CGIAR, IFPRI, WRI, UNEP, UNCCD) with the Google search engine. The search was initially carried out in October and November 2017, with periodic updates through to the end of 2021. Details of all search strings and results are available in Table S1 and Data S2.

Following screening, an initial list of 1390 studies was refined to 60 studies for which we carried out data extraction, compilation, and harmonization to maximize the available data size and quality. We developed a comprehensive database (Data S1) of published global food system model scenarios for 2050 with impact estimates for 10 environmental indicators representing four planetary boundaries (land-system change, freshwater use, climate change, and biogeochemical flows). For 37 studies representing 1,878 future projections and 844 scenario storylines, we assembled a full dataset of input parameters that contained the minimum set of 28 quantitative variables (Table S5) necessary to parameterize all interventions (Table 1). All quantitative variables were either extracted directly from each publication (including supplementary material or code), directly obtained from the lead authors of each study, or derived from data provided by the authors [see (*27*) Section 2.1]. This unique dataset provided the input for training the meta-regression models (see below).

Defining food system specific environmental limits

We then defined food system specific environmental limits for four planetary boundaries for the year 2050 based on the latest scientific consensus on global environmental limits and other literature [see (*27*) Section 1.2]. We selected 10 environmental indicators and specified environmental limits based on available model outputs in the literature, as well as on current scientific consensus around planetary boundaries (*1-3, 7*). Uncertainty in environmental limits was incorporated by specifying triangular (or Gaussian) probability density functions (PDFs), both commonly used in risk analysis (*92*), characterized by best estimate, minimum (or -2SD), and maximum (or +2SD) values. Triangular distributions were fitted to data on food system specific environmental limits (Table S2) with the R package *propagate* (*93*) using unweighted residual sum-of-squares as the minimization criterion. Where a best estimate was not available, we used the mode value calculated as *3*mean(x)-min(x)-max(x)*, to allow the fitting of a triangular distribution. For the climate change boundary, we used data from the AR6 Scenarios Database (*36*), which contained 260 scenarios with total direct emissions from agriculture (CH_4 + N_2O + net CO_2 emissions from land use and land-use change) compatible with a 67% and 50% chance of remaining within 2.0 and 1.5 °C, respectively (*73*). After fitting alternative distributions and comparing their fit based on the Bayesian information criterion using the *propagate* (*93*) package, we selected a normal distribution due to its better fit and ease of use and interpretation compared to alternative candidate distributions.

For climate change, freshwater use, and $P_{instream}$, environmental limits also account for the possible trajectories of non-food sectors which exert a significant pressure on those boundaries (Table S2). The PDF representing the environmental limit for climate change already encompassed assumptions around the emission trajectories of non-food sectors and therefore the underlying scenarios were compliant with global emissions targets. For freshwater use and $P_{instream}$, we specified the potential impact of non-food sectors (household and industry in the case of freshwater use, and sewage in the case of $P_{instream}$) via a best estimate coupled with minimum and maximum estimates, and used these to modify the relevant food system specific environmental limits. Our environmental limit PDFs thus encompassed the inherent uncertainty in defining the Earth system's safe operating space (*1*, *2*), as well as the range of possible trajectories of relevant non-food sectors and the potential share of each planetary boundary available to the food system in 2050 [see (*27*) Section 1.2].

Meta-regression modeling and scenario predictions

We developed linear mixed-effects meta-regression models to synthesize global food system impacts on the planetary boundaries based on the database of scenario projections assembled from the 60 systematically selected studies (Data S1) and used these statistical models to generate a comprehensive database of predictions for 2050 [see (*27*) Section 1.4, Data S4]. We used a random intercept model design with the model version used in each study as the random effect term to reduce the bias resulting from large differences in the number of published scenarios between studies, and control for the lack of independence between scenarios within each study or studies using similar runs from the same food system model. Following (*94*), we fitted 10 linear mixed-effects models (LMMs), one for each environmental indicator using a restricted maximum-likelihood routine implemented in the R package *lme4* (*95*).

To fit the LMMs for all indicators other than CO_2 LUC, we used the log response ratio of environmental impact computed as *ln (future estimate/base year estimate)* as the response variable. The independent variables (Table S5) representing relevant demand- and supply-side interventions for each environmental indicator were specified as fixed-effect regressors. We pre-processed independent variables to control for differences in starting values by harmonizing units, and calculating multipliers relative to the base year (for population, diet, crop yields, feed conversion ratios, emissions intensity, water-use efficiency, nutrient-use efficiency), absolute percentages (for waste, feed composition and nutrient recycling), and absolute values (for carbon price). For CO_2 LUC, the data compiled from the selected studies (Data S1) was not sufficiently comparable in scope to allow harmonized predictions compatible with the AR6 Scenarios Database (*36*). We instead trained an LMM using 4729 vetted 2010-2050 observations in the AR6 Scenarios Database (*36*), with the land-system model as the random effect term, 5-year averaged annual CO_2 LUC emissions from agriculture as the dependent variable, and carbon price, year, and 5-year averaged annual change in cropland, pasture, and forest cover as independent variables (Table S14).

We carried out model selection and validated prediction accuracy through cross-validation, following best practice for predictive models (*96*). We used *repeated cross-validation*, repeating the cross-validation 5 times with alternative fold numbers (over the range 3:*k*, where *k* was the number of random factors minus 1), implemented in the R package *cvms* (*97*) which explicitly controls for the random effect structure in LMMs. We first formulated alternative model structures ranging from the least parsimonious (all relevant variables used as independent predictors, e.g., population and per capita demand for ruminant meat), hybrid (partial aggregation of predictors, e.g., per capita caloric demand for ruminant meat multiplied by population) to the most parsimonious (based on a process-based logic using aggregates of independent predictors, e.g., total feed demand for ruminant meat) [see (*27*) Section 2.3]. The parsimonious models outperformed the other models based on the *root mean square* metric and hence, were selected and screened for further analysis. We used *variance inflation factors* to test for collinearity and likelihood-ratio tests to further refine the selection of fixed-effect predictors. During this stage we also tested the addition of an initial condition delta as per (*16*) which improved the fit for the cropland, blue water, methane, nitrous oxide and N_{fert} models. Further tests and outlier handling were performed to exclude any bias in the model coefficients due to violations in the homogeneity of residual variance or influence from outliers in the models using the *robustlmm* (*98*) and *LMERConvenienceFunctions* (*99*) packages [see (*27*) Section 1.4 & Section 2.4].

We then generated predictions using the fitted LMMs encompassing combinations between all relevant interventions at each level of ambition (Fig. 1B, Table 1). Mean predictions and prediction intervals were calculated using a simulation function in the R package *merTools* (*100*) that draws a sampling distribution for random and fixed effects and then estimates the fitted value across that distribution, providing an efficient approximation to a parametric bootstrap. We used 2000 samples to calculate the 95% prediction interval around the mean, incorporating uncertainty of random and fixed effects, as well as residual variance from the model. We then averaged the prediction intervals to derive normal distributions for each prediction. Predictions in log response ratios were converted to percentage change and multiplied by 2010 base year values (Table S25) to derive projections in absolute units for 2050.

Risk assessment

Mean predictions of the impact of interventions across each of the 10 environmental indicators were used to calculate the risk of exceedance of environmental limits for all combinations of interventions and levels of ambition (i.e., predictor variables) (Fig. 1A). Combining uncertainty in both the predictive models and the environmental limit PDF, the risk of exceedance was calculated as:

$$ER_{i,j} = P(Y_{i,j} > X_j)$$

where *Y* is the normal distribution of the modelled prediction interval for each intervention combination *i* and indicator *j*, and *X* is the PDF of the environmental limit for each boundary (in the case of land-system change, climate change, and freshwater use) or indicator (for N_{fert}, $N_{surplus}$, P_{fert}, $P_{instream}$) *j*. We then calculated intervention-level averages by summarizing (mean and standard deviation) risk across each planetary boundary (Fig. 2), and percentage deviation and predictions in physical units for each indicator (Fig. S4, Fig. S5).

To identify intervention combinations that met IPCC-calibrated uncertainty risk thresholds (*35*), we mapped the performance of all intervention combinations against their risk mitigation and ambition level. We did this both individually, for each of the four planetary boundaries, and combined across all boundaries, yielding a total of 2,097,152 plausible intervention level combinations across boundaries (Fig. S6). We then selected the scenarios that met the < 0.50 risk (exceedance *about as unlikely as not*) and < 0.33 risk (exceedance *unlikely*) thresholds compatible with the calibrated uncertainty language applied by the IPCC in its assessments (*34*, *35*). We finally analyzed the selected intervention combinations to identify the option space available in terms of the type and level of ambition of interventions required to reduce the risk of exceedance of the Earth's safe operating space.

Acknowledgments

We are grateful to D. Driscoll and E. Ritchie for comments on earlier versions of the manuscript. We also acknowledge other individuals listed in Data S1 (see Github/Zenodo links) for data contributions and helpful correspondence related to data quality. The work was supported by Deakin University.

Data availability

All input data and code to replicate the analysis are freely available and can be accessed through the following open access Github repository: https://github.com/MichalisHadjikakou/GFSI-MRM. The version of the model used to produce all results presented in the manuscript is stored in the following Zenodo release: https://doi.org/10.5281/zenodo.7772720. Extended results for each environmental indicator and planetary boundary are available at: https://doi.org/10.5281/zenodo.7772750.

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Supplementary Materials for

Mitigating risk of exceeding environmental limits requires ambitious food system interventions

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1 Materials and Methods

1.1 Systematic review and meta-analysis protocol

1.1.1 Protocol

A systematic procedure for study identification and data collection is essential to the development of a meta-analytic forecasting model (*1*, *2*). We followed the guidelines for systematic reviews and meta-analysis in ecology and environmental management (*3*-*7*), based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) protocol (Fig. S1). The PRISMA protocol is a set of established principles and guidelines aimed at minimizing bias and ensuring scientific validity and reproducibility (*8*-*11*). Evidence of all search strings, search results, and data extraction associated with each selected study and its characteristics is provided in Data S1 and S2.

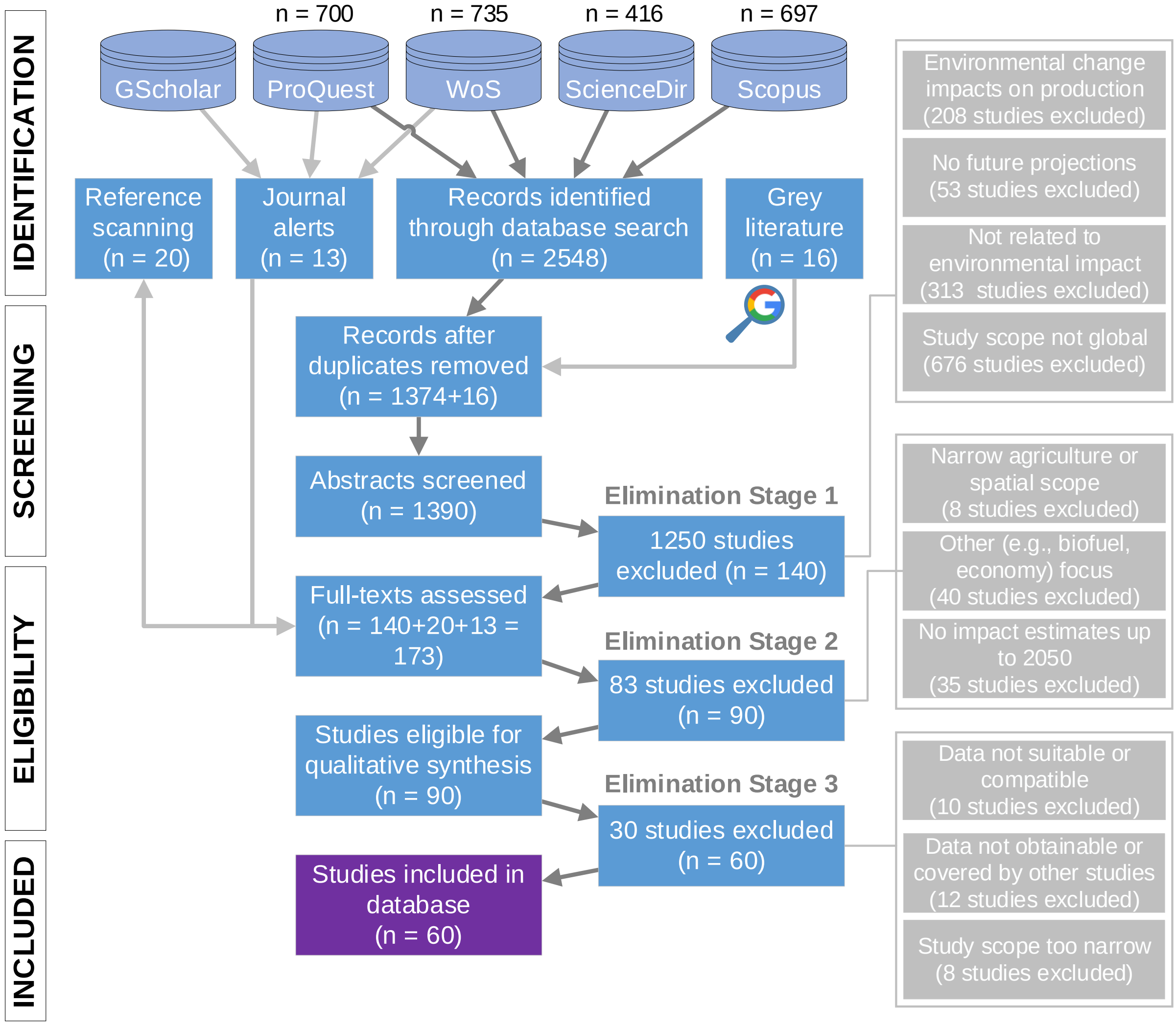


Fig. S1. Summary of the literature search and the study identification and screening process following the PRISMA protocol (*8*) (for study details see Data S2).

1.1.2 Problem formulation and scope

The systematic literature search supported all three primary objectives of this study:

1. To determine the key environmental indicators, interventions, and scenario drivers (quantitative variables) employed in modeling studies with quantitative estimates of future environmental impacts of the food system with a time horizon of at least up to 2050.
2. To develop a meta-regression model to robustly quantify the technical risk mitigation potential of the future global food system exceeding the four planetary boundaries of land-system change, climate change freshwater use, and biogeochemical flows (*12, 13*) under different food system scenario intervention combinations.
3. To extract qualitative information on the necessary actions that enable different food system interventions.

Given the wide scope, diverse methods, and thematic heterogeneity of studies assessing future environmental impacts of global food system scenarios, our meta-regression model synthesizes and draws broad generalizations from a large number of studies to provide robust effect sizes of intervention impact compared to those that can be ascertained from any individual primary study (*6*). Framing of the research question was defined using the Problem-Intervention-Comparator-Outcomes (PICO) framework (*6, 14*):

- Problem: the future environmental impact (for four planetary boundaries) of the global food system (food production) with a time horizon of at least up to 2050. There is considerable variation between studies with respect to the scope of the system (i.e., most studies concentrate on agricultural impacts but some also cover the food supply chain), handling of crop and livestock systems, and coverage of terrestrial and marine domains. We limited the scope of this study to studies that estimate global-scale environmental impacts relevant to planetary boundaries associated with land-based food production, including inputs to aquaculture but excluding their marine impacts.
- Intervention(s): any policy, measure or management strategy taken to reduce the environmental impacts of food production at a level of ambition that exceeds business-as-usual (BAU). These were broadly categorized as either Supply-side (e.g., improved productivity, resource-use efficiency, supply-chain efficiency), Demand-side (e.g., reduction in aggregate food demand, changes in consumption patterns), and Integrated (combinations of Supply-side and Demand-side interventions).
- Control or Comparator: the business-as-usual (BAU) or reference scenarios, as defined by each study, serve as the control group that defines whether a certain policy can be classified as an intervention. These tend to be based on status quo or trend projections of population growth, or agricultural efficiency and diets. Several studies use FAO projections (*15, 16*) for their BAU scenarios.
- Outcomes: meta-regression models capable of estimating the effect size and risk mitigation potential of 10 key food system interventions for 10 individual planetary boundary indicators representative of four planetary boundaries (*17-19*).

1.1.3 Literature search

We identified primary research published as peer-reviewed journal articles and grey literature (major reports) containing quantitative estimates of future food system environmental impacts of relevance to planetary boundaries. We restricted our search to studies written in English that were global in scope and published on or after January 2000.

Studies focusing on qualitative assessment of the future food system that did not involve primary research were not used as a source of quantitative data (Section 1.1.4).

The search strategy was refined from August to September, 2017, using the ProQuest Natural Science Collection, selected because it includes the US Department of Agriculture's Agricola database. The final search string was then adapted to another three databases (Scopus, Web of Science – Core Collection, Science Direct – All Sciences) and implemented from October to November, 2017. The use of multiple reputable online databases ensures comprehensiveness (*20*). Alerts were also set up using the final search string and study co-authors were also engaged to ensure that relevant articles published during the write-up of the review for which the data was obtainable have also been included. This allowed for periodic updates through to the end of September 2021. The initial part of the search was restricted to peer-reviewed scholarly journal papers, conference proceedings, and book chapters.

A test list of 20 highly cited articles was established covering prominent global food system modeling research groups and authors (Data S2). This was used to establish an initial search string and to progressively refine the search strategy by assessing the extent to which the search strategy correctly retrieved articles in the test list (*9*). The search was based on four concepts:

1. Relevant to some aspect of the food system;
2. Includes future scenarios;
3. Assessed environmental impact relating to planetary boundaries, and;
4. Global in scope.

Several keywords and phrases were developed for each of these concepts and these were linked by an OR Boolean operator in the search strategy to capture the potential for different usage, wording, and spelling, and thereby ensure a comprehensive coverage. In turn, the four concepts were combined by an AND Boolean operator to ensure to studies captured all four concepts (see Table S1 for search strings and Data S2 for full search history).

Search results were exported from ProQuest as spreadsheets and the percentage of test list articles retrieved in each search was assessed in order to optimize the search string. An initial 20% retrieval rate using ProQuest alone was improved to >50% when using the final search string. Ultimately an 80% retrieval rate (16/20 test list articles found) was achieved after search results from all four databases were combined (Data S2). No further refinements to the search string were made after this point to prevent a significant increase in the number of retrieved studies (over 5000) with little improvement to the overall retrieval rate of relevant articles. A total of 2548 studies (journal articles plus book chapters) were exported to Endnote for abstract screening (Fig. S1).

An anticipated challenge was to ensure adequate coverage of the grey literature given its importance in this research space (*21*). Further literature searches were conducted to retrieve relevant grey literature from reputable institutions using a simplified version of the final search string in the Google search engine. Further searches were conducted by adding a URL domain restriction such as those belonging to specialist organizations such as the FAO, World Bank, CGIAR, IFPRI, WRI, UNEP, UNCCD. A recent review article (*22*) was also used to identify additional reports from the grey literature. A total of 17 such reports were retrieved and exported to Endnote for further screening (Fig. S1).

Table S1. Main concepts and refined universal search string used to retrieve peer-reviewed publications (only original peer-reviewed articles not including reviews) published on or after 1 January 2000 (all = all fields, ab = abstract only, ti = title only). Full search history and article test list are available in Data S2.

Search concepts	Search string	Justification
Concept 1 "Food system"	ti(food OR "agricultur*" OR "diet*" OR "feed*" OR "fish*" OR "aquaculture" OR "livestock" OR "meat*" OR "crop*")	Allows capturing all key elements of food production
Concept 2 "Future"	ti("future" OR "project*" OR "scenario*" OR "outlook*" OR "forecast*" OR "trend" OR "demand*" OR "trajector*" OR "2050" OR "2100" OR "2025" OR "2030" OR "2035" OR "2040" OR "2045")	Specifies the preference for studies with future predictions as opposed to current impacts
Concept 3 "Environmental impacts/indicators"	ti("environment*" OR "sustainab*" OR "footprint*" OR impact* OR "resource*" OR "water" OR "land*" OR "nitrogen" OR "N" OR "phosphorus" OR "P" OR "carbon" OR "greenhouse gas" OR "soil" OR "bio*" OR "ecolog*" OR "ocean*" OR "marine" OR "climat*" OR "ozone" OR "planetary boundar*")	Lists all commonly used environmental indicators which relate to the planetary boundaries
Concept 4 "Global, not regional"	ab("glob*" OR "international*" OR "region*" OR "planet*" OR "human*" OR "world") NOT ti("Chin*" OR "USA" OR "US" OR "United States" OR "Europe*" OR "Mediterr*" OR "UK" OR "United Kingdom" OR "Ind*" OR "Braz*" OR "Afric*" OR "Asia*" OR "Americ*" OR "Middle East*" OR "Austr*" OR "Jap*" OR "Nig*" OR "Russ*" OR "Bang*" OR "Canad*" OR "Germa*" OR "Pak*" OR "Thai*" OR "Malay*")	Excludes regional/local studies. Any studies with country or region name in the title have been eliminated (only possible in Scopus and Web of Science; not possible in ProQuest or ScienceDirect)

1.1.4 Article screening

After removal of duplicates, the titles and abstracts of the remaining 1407 studies (1390 journal articles and book chapters plus 16 reports from the grey literature) retrieved during the initial database search stage were examined for relevance to the review question based on the *a priori* inclusion criteria (Fig. S1). The exclusion criteria for the first stage of elimination included:

- articles focusing on climate change or other environmental processes and their effects on food production;
- articles without future projections;
- articles focusing on non-environmental aspects of the food system (e.g., food security, pest management), and;
- articles that did not have a global scope (Fig. S1, Data S2).

140 studies out of those identified in the initial database search were selected for full text screening. During full text screening, the reference lists of selected studies, with an emphasis on the more recent articles and reports (*23, 24*), were used to identify other relevant articles through citation and reference scanning (*9, 10*). Over the course of the entire study, full text screening was carried out for a total of 173 studies including selected studies from the initial database search (140), and studies (journal articles, book chapter or reports) identified through reference scanning (20) and journal alerts (13) (Fig. S1). Studies were assigned randomly for screening by four co-authors, with each article screened independently at least twice. The exclusion criteria for the second stage of elimination included:

- narrow agriculture (e.g., focused on aquaculture or specific crop) or spatial scope (i.e., region- or country- specific);
- other non-food system agricultural focus (e.g., biofuels, fiber crops, yields, economy, health);
- no quantitative environmental impact results or no estimates extending up to 2050 (Fig. S1, Data S2).

A third and final elimination process was carried out on the remaining 90 studies to filter those for which we were not able to obtain the required data, either because the authors did not respond to repeated email requests, or appropriate data was simply not available or extractable (Fig. S1). The exclusion criteria were:

- data not suitable or compatible (i.e., lack of clearly defined intervention scenarios, input variables used not available or consistent with other studies);
- data could not be obtained or already covered by a more recent study
- studies focused on a narrower thematic scope such as a specific domain of the food system (e.g., livestock, fisheries) or the timeframe did not extend to 2050 (Fig. S1, Data S2).

The last elimination stage resulted in a total of 60 studies that met all the inclusion criteria necessary to be deemed appropriate for the database (Data S1). All 60 studies were included in the qualitative synthesis, but only 40 provided training data for the meta-regression models following data quality considerations in the model selection and fitting stage (Section 1.3.2).

1.1.5 Quantitative and qualitative data extraction

Studies that met all criteria for inclusion were used to extract relevant quantitative scenario input (moderator) and output (outcome) estimates (Data S1), in addition to qualitative data on actions underpinning different interventions (Data S3). For each scenario within each study we extracted environmental impact estimates reported for one of 10 environmental indicators representing the four planetary boundaries (*13*, *25*) (see Section 1.2 for choice of boundaries and indicators). This process entailed a thorough scan of the main published study as well as any appendices and supporting information that contained scenario variable/output data. Quantitative data extraction focused on the environmental variables of interest as well as quantitative scenario variables that defined the key interventions (see Data S1 for the full compiled database). This process was iterative since the primary objective was to establish a consistent set of interventions and their associated quantitative input variables (Section 1.3.2). The final list of quantitative variables extracted took into consideration both the prominence of each related intervention as well as data availability. This followed extensive email correspondence with study authors.

The data extracted from each article and any necessary post-processing was checked and validated in close collaboration with study authors. Where necessary (e.g., where specific data was only available in figures or was not available in the text or supporting information), lead/corresponding authors of studies were contacted by email using a standard email template to provide clarification or additional data. Several of the authors who expressed a strong interest to provide additional data (i.e, input variables or intermediate results not shared as part of the original study) and also aided in the validation of other data and calculations, were subsequently invited to co-author our study. Notwithstanding, in a small number of cases some data gaps remain in the final dataset either because of no response from authors, data were not available due to confidentiality reasons, or authors were unable to retrieve old or missing data (Fig. S1, T4 in Data S2). In close collaboration with invited co-authors, we also carried out additional calculations in order to harmonize the highly diverse data types (see Section 2.1, Data S1). This included the following steps:

- Calculating global weighted averages for spatially disaggregated variables or results
- Calculating weighted averages for crop and livestock productivity metrics
- Unit harmonization based on standard conversion factors
- Filling in any missing data based on sources directly cited in the manuscript or directly supplied by study authors

Important qualitative information was also collected from selected studies to enhance coding and classification, and to extract the list of actions that enable each of the interventions considered (Data S3). Qualitative data extraction included the recording of basic study information (e.g., title, authors, year of publication, journal/report name) the modelling framework and the exact version used, and the type of scenarios and interventions employed (see Section 1.3). When assembling the quantitative database (T1, Data S1) we followed the convention in systematic reviews by assigning each scenario to a single row with categories or 'structural dimensions' as columns, including coding to indicate partitioning of studies into appropriate subgroups (*4*, *20*, *26*). The extracted quantitative and qualitative data (Data S1) served as inputs to the meta-regression models (Section 1.4).

1.1.6 Study selection bias

Primary studies were selected on the basis of whether they met the inclusion criteria (Section 1.1.4). To accommodate the diverse modelling approaches and storyline assumptions, we considered all selected studies to be of high quality and the range of available scenarios was taken as representative of the range of uncertainty in plausible food system futures. While some studies provide many more scenario variants than others, our choice of statistical modeling method aimed to minimize any bias towards studies with more scenarios through the use of random effects (*21*) (Section 1.4). We also present sensitivity results that assess the impact of different models on pooled effect size estimates (Section 2.3.3).

Several sources of bias remain in the study selection and data collection processes. First, some degree of publication bias is inevitable. Typically, studies with larger than average effects are more likely to be published, resulting in upward bias effect size estimates (*27*). Indexing bias was tackled through the use of multiple search engines (Fig. S1), while language bias was unproblematic since it is unlikely that global food system scenario studies would be published in languages other than English. Other typical forms of bias in systematic review such as selection, performance, detection and attrition bias (*4*) were not of concern because studies typically distinguished clearly between BAU and intervention scenarios, especially since this could also be ascertained on the basis of the storylines and quantitative variables provided (Table S5). However, reporting bias is likely to be significant in our study. While some studies did not report (*28, 29*) key input or output variables, other studies explicitly shared comprehensive supplementary information and multiple scenarios resulting from sensitivity analysis. While this source of bias could not be completely eliminated, we minimized data information loss by directly contacting study authors and working closely with them to reconstruct input datasets (see Data S1).

1.2 Defining food system specific environmental limits

We specified environmental limits for planetary boundary indicators which quantify the food system's share of the Earth's safe operating space (highlighted in *30*) for the year 2050, allowing, where appropriate, for the potential (and uncertain) environmental impacts of the rest of the economy (Table S2). For the purposes of this analysis we concentrated on the four planetary boundaries for which outputs were available, namely Climate Change, Land-System Change, Freshwater Use, and Biogeochemical Flows (*13, 25, 31*). The choice of ten planetary boundary control variables (hereafter referred to as *indicators*) reflects current scientific consensus (*13, 17-19, 30*) and the nature and availability of information from conventional models and forecasting tools for our target year (2050). In each case we sought to extract as many indicators as possible to maximize the coverage of each planetary boundary while ensuring adequate sample sizes to allow statistical analysis.

For each planetary boundary indicator, we identified the best estimate for the safe global limit, along with minimum and maximum values based on a literature review of recent published estimates. To capture the considerable scientific uncertainty in published values for environmental limits, we used the minimum, maximum, and best estimate to specify triangular probability density functions. Triangular distributions provide an intuitive way to represent uncertainty in a process with central tendency (i.e., best estimate) constrained by finite bounds (i.e., minimum/maximum estimates) and are often employed to quantify uncertainty in risk analysis (*32-34*). In the case of the Climate Change boundary, where a large number of scenario runs compliant with a boundary were available through the AR6 Scenarios Database (*35*), we trialed alternative distributions and settled on a normal distribution instead of a triangular distribution.

Distributions were fitted to the best available data on food system specific environmental limits (see Table S2 for sources) with the R package *propagate* (*36*) using unweighted residual sum-of-squares as the minimization criterion. We carried out sensitivity analysis by varying the bin number and setting the number of bins as defined by the Freedman–Diaconis rule (*37, 38*). The final parameters (*min*, *mode*, *max* for the triangular distributions and *mean*, *standard deviation* for the normal distribution) were selected from the distribution that displayed the best goodness-of-fit as indicated by the lowest Bayesian Information Criterion value (*37, 38*). Where a best guess (mode) value was not available, we used the actual minimum and maximum along with either the mode estimated as *3*mean(x)-min(x)-max(x)*, or simply using the mean value as the mode (in cases where the mode calculation yielded results outside the min-max range), to allow the fitting of a triangular distribution (Table S2).

For time-sensitive planetary boundaries for which an agriculture-specific environmental limit for 2050 had not been previously established (*19*), and for which non-agricultural sectors of the economy would also be expected to have a significant time-dependent environmental impact trajectory, we also accounted for the uncertainty in the food system share. This was the case for Land System Change, Climate Change, Freshwater Use and Biogeochemical Flows (P). This share accounted for the range of possible future trajectories for both the agri-food sector and for all relevant non-agricultural sectors such as energy, transport, and manufacturing in the case of Climate Change, household and industry in the case of Freshwater Use, and household waste and sewage in the case of Biogeochemical Flows (P). In the case of Climate Change we did not have to explicitly calculate a share because we were able to filter out the Agriculture component of Agriculture, Forestry, and Other Land Use (AFOLU) of scenarios compliant with emissions trajectories with a >50% chance of limiting warming to 1.5°C or >67% chance of limiting warming to 2.0°C from

(*35*), that are in harmony with storyline assumptions about the necessary decarbonization of the broader economy (*39, 40*).

While we acknowledge that the values underpinning the global environmental limits for planetary boundary indicators remain the subject of considerable research and refinement (*41*), here we only considered their global limits (see Section 2.4). Despite significant regional heterogeneities and uncertainties in proposed thresholds (*42, 43*), adherence to global limits is a central premise of the planetary boundary framework (*17, 44, 45*). Our food-system specific environmental limit estimates encompass the uncertainty in current scientific knowledge of the safe operating space for each indicator (*13, 17, 19*), as well as uncertainty in the possible future trajectories of environmental impacts of society and the economy (Table S2).

Table S2. Food system-specific environmental limits for planetary boundary indicators in 2050. Includes the mode (best estimate), minimum, and maximum values defining the probability density functions used to represent uncertainty in environmental limits and a description of literature sources and assumptions.

Indicator	**Env. limits (best estimate, low, high)**	**Sources**	**Rationale**
			Land-System Change
TotalAgArea Total agricultural area (i.e., cropland + pasture)	<3309 Mha (3019 - 5460)	(*17, 46*)	The total land area under agriculture (i.e., cropland and pasture) serves as the overall control variable for the food system as it relates strongly to the amount of forest cover remaining, with major forest biomes having a key role in land surface-climate coupling (*13, 17, 47*). Following (*46*), limits for total agricultural area are based on the premise that 54-75% (3466-4790 Mha) of global forest cover must be maintained, based on the weighted average potential area across the three major forest biomes (tropical, temperate, boreal) (*17*). For consistency with the majority of the studies in our database and existing estimates (*46*), we source all figures from FAOSTAT (*48*), while acknowledging that other widely used cropland and pasture estimates (*49*) would yield slightly different boundary estimates. Since the total area of agricultural and forest land equalled 8926 Mha in 2010, and assuming the remainder of the planet's land area (4093 Mha), also termed 'Other land' in FAOSTAT, is unsuitable for afforestation and/or agriculture, the environmental limit for total agricultural area calculated as the sum of cropland and pasture was 4136 Mha (which matches the value proposed by *46*), with a 75-54% (41.35 – 54.60 Mha) zone of uncertainty as suggested in (*17*). In line with our overall methodology of deriving 'flexible' agriculture PB shares in future to accommodate for uncertainty in the trajectories of other sectors in future storylines, an allowance for additional constraints on forest cover from other non-agricultural drivers of deforestation (*50*), namely mining, infrastructure and urban expansion, should also be considered in deriving limits for agriculture. We did not consider the more detailed biome-level boundary (*17*) as our analysis was global in scope. Following a review of the literature on the relative influence of key deforestation drivers, we sourced values for the shares of deforestation attributable to agriculture (cropland and pasture expansion) (*24, 50-53*). In line with recent studies (*13, 28, 29, 54, 55*), we included both commodity-driven (commercial) and subsistence agriculture, even though the latter may often only lead to temporary forest loss, as determined by Curtis et al. (*50*) using satellite imagery covering the period 2001 to 2015. The often-cited figure of 80% of deforestation driven by agriculture is based on FAO data for Africa, Latin America and Asia for 2000-2010 and originates in (*52*), and is consistent with older estimates from the 1980s and 1990s (*53*). Based on similar data, Hosonuma et al. (*51*) calculate 73%, with the remainder attributed to mining (7%), infrastructure (10%), and urban expansion (10%). The more recent estimates in Curtis et al. (*50*) did not explicitly distinguish between commodity-driven deforestation for agriculture and other sectors (mining and energy infrastructure) and have therefore not been used in the determination of possible boundary shares. Considering future projections, some future storylines consider that deforestation for reasons other than agricultural expansion will decrease to zero in 2020, as is the case in SSP1 in (*24*). We therefore defined the maximum share as 100%. The mode of the triangular distribution (best estimate) was calculated by multiplying 4136 Mha by the widely used 80% estimate (3309 Mha), while the minimum used the same

Indicator	Env. limits (best estimate, low, high)	Sources	Rationale
			area estimate and the more conservative 73% share (3019 Mha). The high estimate assumed 100% of the remaining boundary would be afforded to agriculture.
			Freshwater Use
Water Blue water (i.e., surface water + ground water) consumption by agriculture	<2274 km^3 yr^{-1} (685 - 4044)	(*13, 17-19, 24, 56-62*)	Consumptive blue water use for agriculture (irrigation and livestock) provides a metric of net use of water that directly matches the Freshwater Use control variable. Based on future water resources projections across economic sectors, we adjusted the overall limit to accommodate non-food societal needs, a notion also compatible with (*63*). The range in projected water consumption by other higher value water users such as industry and households (*24, 56, 60*) considerably reduces the safe operating space for agriculture. Unlike previous studies (*19, 64*), in specifying the food system's share of the planetary boundary for water, we accommodate the range of possible futures in demand from industrial and domestic uses, expected to more than double by 2050, relative to a 2000 baseline (*65*). Note that this estimate (*65*) and other earlier estimates (*66*) refer to water withdrawals as opposed to consumptive water use, hence they were not employed directly in the derivation of food system environmental limits. While a considerable number of studies have estimated future non-agricultural water withdrawals (*61, 65-68*), only a few studies have carried out scenario projections of non-agricultural blue water consumption (*24, 56-61, 69*). Using a total of 9 study-averaged agriculture share estimates (derived from a total of 36 individual scenarios) for 2050 from the aforementioned studies in addition to (*19*) and a widely cited projection for 2025 (*62*) used in (*19*), we calculated minimum, average and maximum shares of total blue water consumption (min=62.3%, max=89.9%, mode=81.2%). These were then multiplied by the triangular distribution of the conservative total Freshwater Use boundary (min = 1100, max = 4500, mode = 2800) proposed in (*19, 64, 70*) to yield a most likely estimate of 2274 km^3yr^{-1} (with a range of 685 to 4044).
			Climate Change
$DirNonCO_2$ Direct on-farm non-CO_2 (CH_4+ N_2O) GHG emissions	<4.74 $GtCO_2e$ yr^{-1} (SD = 1.88) *Estimated using AR6 GWP100 factors*	(*35*)	The food system is an important driver of humanity's overall impact on the Climate Change planetary boundary but given current reliance on fossil fuels, it is not the main driver (*13*). Thus, the Climate Change planetary boundary must be shared between the food system and other sectors, notably energy and transport, and the food system's share of the total GHG emissions budget could increase over time in scenarios where other sectors decarbonise more rapidly (*71, 72*). Recent studies have proposed agriculture-specific or food system specific 2050 targets in line with a 2ºC temperature change target by 2100 (*19, 46, 71*). Only non-CO_2 (CH_4 and N_2O) emissions were considered in these estimates. Here we derived estimates compatible with the recently proposed 1.5ºC warming target (*73*). By selecting a total of 260 target-compliant scenarios from the AR6 Scenarios Database (*35*) we fitted a normal distribution to all compliant scenario projections to establish a direct non-CO_2 annual GHG emissions range for agriculture in 2050. Similar sub-boundaries could be calculated for CH_4 (mean=114.7 Mt, SD = 37.5Mt) and N_2O (mean=4.16 Mt, SD = 1.17 Mt) based on the same 260 scenario runs but we did not directly used these in the analysis. We use standard AR6 GWP100 CO_2e in our calculations, with a value of 27.2 and 273 for CH_4 and N_2O respectively.
$DirNonCO_2LUC$ Direct on-farm non-CO2 GHG + net emissions from land-use and land-use change	<3.53 $GtCO_2e$ yr^{-1} (SD = 3.52) *Estimated using AR6 GWP100 factors*	(*35*)	The food system is the key driver of CO_2 emissions associated with land-use change processes such as deforestation and destruction of peatlands for agricultural purposes (*74*). These can be either positive due to conversion of different biomes to agriculture and consequent loss of terrestrial carbon stocks, or negative resulting from carbon sequestration via afforestation/reforestation (*75-77*). Many models and studies calculate net CO_2 emissions from land-use change alongside direct non-CO_2 emissions (*$DirNonCO_2$*), with their sum (*$DirNonCO_2LUC$*) constituting a major component of the AFOLU classification of national GHG inventories (*78*). We therefore included the land-use change component in our definition of the Climate Change planetary boundary. Using the same 260 scenario runs compatible with >50% chance of limiting warming to 1.5°C or >67% chance of limiting warming to 2.0°C from the AR6 Scenarios Database (*35*), we fitted distribution of total agriculture AFOLU emissions (direct CH_4 + N_2O + net CO_2 emissions from land use and land-use change). The higher range in *$DirNonCO_2LUC$* compared to *$DirNonCO_2$* reflects the higher uncertainty in current and future emissions from land use change including multiple negative emission scenarios and the critical role of afforestation/reforestation in most compliant scenarios (*79-81*).

			We acknowledge that our definition of the Climate Change boundary based on $DirNonCO_2LUC$ only covers direct emissions associated with agricultural production. The food system is responsible for considerable additional emissions including indirect (upstream) emissions from energy and transport, and other inputs to food production such as on-farm energy use from machinery and vehicles (*54*). A number of studies in our database (Data S1) that use GHG data from life-cycle assessments (*40, 82-84*) cover these additional upstream emissions. However, by using an emissions distribution from scenarios with >50% chance of limiting warming to 1.5°C or >67% chance of limiting warming to 2.0°C, we also implicitly assume that decarbonization targets of relevant upstream sectors such as energy and transport are also met.
Biogeochemical Flows			
Nfert Total nitrogen fertilizer application in agriculture	<69 TgN yr^{-1} (52 - 130)	(*19, 64*)	A global environmental limit for nitrogen (N) fertilizer application, as suggested in (*19*) and (*64*), is a considerable upward revision of the previous N fertilizer boundary estimates (*17, 46, 85*) which also included biological fixation. In accordance to the precautionary principle, we selected the lower and best estimate boundary based on updated modeling (*19*) but also made an allowance for potentially higher application of N based on the higher estimate in (*64*), that allows for the increased use of N fertilizer if N is globally redistributed and efficiency of use is improved. As these limits are already food-specific, given also that agriculture's share of total global anthropogenic N is currently estimated at 85% (2), no further adjustment was performed.
Nsurplus Nitrogen surplus from agricultural land (i.e., N inputs minus outputs)	<90 TgN yr^{-1} (50 - 146)	(*19, 46, 86, 87*)	$N_{surplus}$, calculated as the difference between total N inputs (i.e, N fertilizers, N-fixation, animal manure, crop residues, and seeds) and total N outputs (i.e, harvested crops and crop residues), complements the more established N_{fert} control variable by providing a more direct impact indicator of potential N loss from agricultural production systems and the eutrophication risk for natural water bodies that is more responsive to future improvements in nutrient-use efficiency (*29, 46, 88*). Several scenario studies that employ nutrient budget models provide estimates for $N_{surplus}$. The zone of uncertainty for the N loss environmental limit proposed was originally proposed as 50-100 Tg N yr^{-1} based on the lower bound for crop production (*87*) and the maximum for total agriculture suggested by (*86*). As our maximum limit we used the upper range estimate of 146 Tg N yr^{-1} (*19*).
Pfert Total phosphorus fertilizer application in agriculture	<16.0 TgP yr^{-1} (6.2 – 17.0)	(*17, 19, 89*)	Similarly to N_{fert}, the P fertilizer boundary was also revised upwards following recent modeling (*19, 64*). We adopted the mode and maximum limits directly from this newly proposed boundary. In line with the precautionary principle, we also chose to maintain the older lower limit (*17, 46*), proposed in response to the critique of Carpenter and Bennett (*89*) of the original limits for P (*18*) to more comprehensively account for P impacts on both ocean anoxia and freshwater eutrophication. This also closely matches the lower boundary in (*64*) for a worst-case scenario where improved production practices and redistribution are not adopted. As is the case for N_{fert}, this boundary is inherently agriculture-specific, with as much as 96% of all mined P used for fertilizer production (2, 16).
Pinstream Acceptable P load in freshwater (i.e., critical concentration * global freshwater discharge into oceans)	<2.89 TgP yr^{-1} (1.93 – 3.95)	(*17, 18, 90-92*)	Unlike $N_{surplus}$, $P_{surplus}$ is less meaningful as an indicator of environmental impact given the low fraction of surplus that eventually becomes runoff into waterways. It is the latter that represents the major cause for concern due to its association with algal blooms and water column hypoxia (*93*). The P boundary is associated with it in the form of P flow from freshwater systems into the ocean (*17*), in order to provide a specific indicator of the associated risk for large-scale anoxic events (*13, 18, 94*). The total global environmental limit defining the safe operating space for $P_{surplus}$ is set at 11 Tg P yr^{-1} with an uncertainty range of 11 – 100 Tg P yr^{-1}. These limits are not agriculture-specific, which creates an incompatibility with study estimates from agriculture-specific $P_{surplus}$ (*28, 29, 93, 94*). While we also considered an agriculture-specific planetary boundary by comparing the percentage of P export from rivers to the ocean that comes from agriculture based on recent data (*92*), we opted instead for an environmental limit in relation to critical P concentrations in freshwater. This is justified in the basis that P-related eutrophication issues are most prominent in freshwater, with recent studies recommending loss/runoff to surface water as suitable control variable (*46*). To derive critical P instream loads in freshwater, we first sourced estimates of discharge volume from waterways to the ocean for different SSPs from (*92*) who use an integrated nutrient and hydrological model. We then considered the range in critical concentration of 50-100 mg P m^{-3} (*19*), taking 75 mg P m^{-3} as the mode of a triangular distribution. We estimated min, max and mode and by multiplying these by the min, max and mode (assuming a triangular distribution) of the discharge distribution estimates to yield an estimate of 2.89 Tg P yr^{-1} (1.93 – 3.95 Tg P yr^{-1}). Since none of the studies other than (*92*) report a value for $P_{instream}$ load, we converted model predictions from $P_{surplus}$ to $P_{instream}$ by applying the following formula:

$$P_{instream} = ((P_{surplus} * frP_{surplus}) + (P_{surplus} * frP_{surplus} * frP_{mouth}))/2$$

where $frP_{surplus}$ (min = 0.344, mean = 0.435, max = 0.510) is the fraction of $P_{surplus}$ that becomes runoff and frP_{mouth} (min = 0.403, mean = 0.413, max = 0.418) is the fraction of P river load that becomes P export at the mouth of the river (*92*). Dividing by 2 assumes that the value most comparable with the $P_{instream}$ critical load is the average of P runoff into the waterway and P export to the ocean.

1.3 Systematic review of scenarios and interventions

1.3.1 BAU and broad intervention scenario families

Global food system studies typically quantify plausible future food demand, agricultural production, and associated environmental impacts, using scenario analysis and computer-based simulation models of food system futures. Food system studies and scenarios tend to be complex and highly heterogeneous, often with many underlying driving variables (or *drivers*) (*95-97*). Quantification of scenarios is based on assumptions about common drivers. Previous reviews (*95, 96, 98-100*) have identified the main drivers including a range of *demand-side* (i.e., population size, dietary preferences) and *supply-side* (i.e., crop yields, livestock productivity, resource-use efficiency, environmental intensity, global trade regime) variables. Scenario typologies proposed for global environmental assessments such as the Shared Socio-economic Pathways (SSPs) have also been employed in classifying food system scenarios (*21, 95, 96*). Via a qualitative assessment of selected studies (Data S1), we identified four intervention scenario families (Table S3) described in more detail below.

Table S3. Summary of the main characteristics of broad scenario families as defined for the purposes of this study. Note that "Various" could represent an increase, decrease, or no change in mitigation ambition.

Intervention family	**Level of mitigation ambition**	
	Supply-side interventions	**Demand-side interventions**
BAU	Trend/Constant	Trend/Constant
Supply-side	Higher than BAU	Trend/Constant
Demand-side	Trend/Constant	Higher than BAU
Integrated	Higher than BAU	Higher than BAU

Business-as-usual (BAU) or Trend

BAU or Trend scenarios are typically those where the future is characterized as a continuation of recent historical trends in both demand-side and supply-side interventions (*15, 22, 96, 98*). For example, scenarios such as the IPCC Special Report on Emissions Scenarios (SRES) B2 scenario, the Adapting Mosaic from the Millennium Ecosystem Assessment (MEA), SSP2, and Agrimonde GO all have strong BAU elements (*24, 96, 99*). We therefore consider scenarios as BAU where agricultural production efficiency, food consumption patterns, and their associated environmental impacts follow past or current trends in the absence of any interventions to improve agricultural efficiency or shift diets. These scenarios are typically constructed with intermediate assumptions for non-agriculture specific drivers such as gross domestic product (GDP), or trade openness (*95, 99*). While the concept of a BAU or Trend scenario is consistent across studies, underlying parameter assumptions and model sensitivity can vary substantially, giving rise to significantly different environmental outcomes (*97, 101*).

Supply-side

Supply-side intervention scenarios assume changes in agricultural practices or the food system supply-chain that translate into higher productive efficiency, resource-use efficiency, and environmental intensity relative to the BAU. This includes technological and management interventions that translate into higher crop yields, higher animal feed efficiency, higher nutrient/water use efficiency, lower GHG emissions intensity, or more open and efficient global trade. Food demand (i.e., population, diet) usually remains at or close to BAU levels (as defined in each study) in this set of scenarios.

Demand-side

Demand-side intervention scenarios focus on the impact of changes in population and food consumption patterns which influence the amount and type of agricultural commodities produced via changes in aggregate demand. These interventions test the effectiveness of a reduction in aggregate food demand via lower population growth, reduced overall caloric demand due to changes in diets or reduced waste, and/or a lower proportion of animal products in the diet (*76, 102, 103*). There is considerable diversity in dietary shift scenarios, ranging from a small (e.g., 10%) reduction in ruminant meat (with or without substitution of other protein sources) to a complete elimination of animal products (e.g., a vegan diet) (*94, 104-106*). Production efficiency usually remains at or close to BAU levels (as defined in each study) in this set of scenarios.

Integrated

Integrated intervention scenarios combine supply-side and demand-side interventions. They usually entail some improvement in agricultural efficiency in combination with changes in food demand (e.g., a reduction in the share of animal products in global diets). While in many studies integrated scenarios represent 'all-in' scenarios that stack several interventions at the highest levels of mitigation ambition, this may not be the case. They usually entail some improvement in agricultural efficiency in combination with changes in food demand (e.g., a reduction in the share of animal products in global diets). As with the Supply-side and Demand-side scenarios, there is a considerable range in the scale and intensity of interventions (*19, 23, 46, 76*).

1.3.2 Key interventions and associated quantitative variables

An important prerequisite for training meta-regression models for each environmental indicator (Section 1.4) was compiling a comprehensive dataset of interventions as predictor variables and their impact on different environmental indicators (Table S4.). This extends the more aggregated classification of intervention family (i.e., BAU, Supply-side, Demand-side, Integrated).

To identify the major interventions and predictors for meta-regression models, we first reviewed and mapped all on-ground mitigation actions suggested in the 60 systematically selected studies (Section 1.1, Table S4.). We started with a detailed scan, extracting all suggested interventions (those specifically parameterized in each model plus those mentioned qualitatively in the discussion) using the authors' original terminology. Each paper was scanned twice by different authors to ensure a comprehensive coverage of mitigation actions. This initial collation produced a varied set of actions, of varying specificity. Where vague interventions were made with a reference to the literature, we consulted that reference for additional detail. We then summarized the more than 200 specific on-ground mitigation actions to 59 by combining overlapping ones such as reduced tillage and residue retention into a more comprehensive action (e.g., soil conservation). We grouped the final set of on-ground mitigation actions into five categories according to their supply-chain scope as defined in (*82*) (Data S3).

While it was not possible, given the global scope of the analysis, to capture the entire range and diversity of available on- and off-farm mitigation actions with our chosen set of predictors, we considered those most influential and commonly assessed in food system scenario studies (*22, 95, 96, 99*). We used the list of detailed on-ground actions to identify major interventions, each of which could be modelled based on quantitative predictor variables (Table S4., Data S1). We then assessed whether relevant variables could be extracted from available material (main paper, supplementary information, or code) or sourced directly from the study authors, that would allow the effect of each intervention to be quantified. By comparing and harmonizing extracted data across studies we established a minimum set of 28 aggregated quantitative variables that could serve as proxies for modeling all major interventions (Table S5). Several studies had more detailed data that were subsequently aggregated to match the minimum set specified in Table S5. Interventions that could not be fully parameterized were organic agriculture, trade openness, and disruptive technology (Data S1). These interventions had insufficient data to allow their consideration as unique quantitative predictors but their potential influence could be partly controlled for through other variables such as crop yields, diet, feed efficiency, nutrient-use efficiency, and nutrient recycling.

Table S4. All selected studies, environmental indicators (Section 1.2), and interventions (Section 1.4.2). ‘Y’ = included in meta-regression models, ‘N’ = excluded from meta-regression models. ‘T’ = Trend/BAU projection, ‘X’ mitigation in excess of trend, ‘V’ = mitigation in excess of trend including vegan/vegetarian (Diet column only). Climate action (EI) refers to reductions in non-CO_2 (CH_4 & N_2O) greenhouse gas (GHG) emissions intensity, while climate action (LUC) indicates explicit modelling of efforts to protect and restore natural ecosystems. See Data S1 for additional details and quantitative information.

Study details			**Boundary/Indicator**												**Interventions**										
			Climate Change			**Land-System change**				**Biogeochemical Flows**				**Demand-side**			**Supply-side**							
ID	**Study**	**Meta-regression**	CH_4	N_2O	CO_2 LUC	Cropland	Pasture	Forest	Water	Nfert	Nsurplus	Pfert	Psurplus*	Population	Diet	Waste reduction	Crop yields	Feed efficiency	Feed composition	Climate action (EI)	Climate action (LUC)	Water use efficiency	N & P use efficiency	N & P recycling
1	Davis et al. (2016)	Y				Y	Y		Y	Y				T	V		T	X	T	X		X	X	
2	Lassaletta et al. (2016)	N									Y			T	-		T						X	
3	Schader et al. (2015)	N				Y	Y		Y		Y		Y	T	X		T		X					
4	Bajzelj et al. (2014)	Y	Y	Y	Y	Y	Y	Y		Y				X	X	X	X	X	X	X		X	X	
5	Alexandratos & Bruinsma (2012)	N				Y	Y		Y	Y		Y		T	T		T	T				T	T	
6	Bennetzen et al. (2016)	N			Y									T	-		X	X		X				
7	Bodirsky et al. (2014)	Y				Y				Y	Y			X	X	X	X	X	X				X	X
8	Bodirsky et al. (2012)	N				Y				Y	Y			X	X		X	X	X				X	X
9	Bouwman et al. (2013)	Y								Y	Y	Y	Y	T	-			T	T				T	X
10	Damerau et al. (2016)	Y							Y					T	X									
11	de Fraiture & Wichelns (2010)	Y				Y	Y		Y					T	-		X					X		
12	Lwin et al. (2017)	N										Y		T	-									X
13	Odegard & van der Voet (2014)	Y				Y	Y			Y		Y		X	V	X	X		X			X	X	
14	Pfister et al. (2011)	N				Y	Y		Y					T	X	X	X					X		
15	Conijn et al. (2018)	Y	Y	Y		Y	Y	Y		Y	Y	Y	Y	T	X	X	X	X	T	X			X	X
16	Tilman et al. (2011)	N				Y				Y				T			X						X	
17	Springmann et al. (2016)	N												T	V					T				
18	Springer & Duchin (2014)	N				Y	Y		Y					T	X		X	X				X		
19	Tilman & Clark (2014)	Y				Y								T	V	X	X	X						
20	Roos et al. (2017)	Y	Y	Y		Y	Y							T	V	X	X	X	X					
21	Heck et al. (2018)	Y				Y	Y	Y	Y					T	X		X							
22	Mogollon et al. (2018a)	Y								Y	Y			X	X		X	X	X				X	
23	Mogollon et al. (2018b)	Y										Y	Y	X	X		X	X	X				X	X
24	Powell & Lenton (2012)	N				Y	Y							T	X	X	T							X
25	Muller et al. (2017)	Y	Y	Y	Y	Y	Y		Y		Y		Y	T	X	X	X		X					
26	Stehfest et al. (2009)	Y	Y	Y	Y	Y	Y							T	V		X	X	T	X				
27	Metson et al. (2012)	N										Y		X	V									
28	Popp et al. (2010)	N	Y	Y										T	X			X		X			X	
29	Valin et al. (2013)	Y	Y	Y	Y	Y	Y	Y						T	T		X	X	T					
30	Ronzon (2014)	N				Y	Y	Y						X	X		X							
31	Pradhan et al. (2013)	N												T	X		X			X				
32	Pradhan et al. (2015)	Y								Y		Y		T	X		X	X		X			X	
33	IAASTD (2009)	N				Y	Y		Y					T	-		X							
34	Wood et al. (2004)	N								Y				-	T								X	
35	PBL (2012)	N				Y	Y	Y		Y	Y	Y	Y	T	X	X	X	X					X	X
36	Bouwman et al. (2009)	Y								Y	Y	Y	Y	X	X		X	X	X				X	X
37	MEA (2005)	N				Y		Y		Y	Y			X	X		X	X					X	
38	CIRAD (2016)	Y				Y	Y	Y						T	X	X	X	X	T					X
39	Popp et al. (2017)	N				Y	Y							-	-									
40	UNCCD (2017)	N				Y	Y	Y	Y	Y				X	-	X	X	X				X		

Study details			Boundary/Indicator											Interventions										
			Climate Change			Land-System change				Biogeochemical Flows				Demand-side			Supply-side							
ID	Study	Meta-regression	CH_4	N_2O	CO_2 LUC	Cropland	Pasture	Forest	Water	Nfert	Nsurplus	Pfert	Psurplus*	Population	Diet	Waste reduction	Crop yields	Feed efficiency	Feed composition	Climate action (EI)	Climate action (LUC)	Water use efficiency	N & P use efficiency	N & P recycling
41	Ercin & Hoekstra (2014)	Y							Y					X	X			T	T			X		
42	Doelman et al. (2018)	Y	Y	Y	Y	Y	Y	Y						X	X	X	X	X	X	X	X			
43	Van Vuuren et al. (2010)	N										Y	Y	X	X		X	X	X				X	X
44	Hejazi et al. (2014)	N							Y					X	-									
45	Graham et al. (2018)	Y							Y					X	T		X	T				X		
46	Springmann et al. (2018)	Y				Y			Y	Y		Y		X	X	X	X	T		X		X	X	X
47	Willet et al. (2019)	Y				Y			Y	Y	Y	Y		T	V	X	X	T		X		X	X	X
48	Tallis et al. (2018)	N				Y	Y	Y						T	T		X					X		
49	Weindl et al. (2017a)	Y			X	Y	Y	Y						T	X		X	X	X		X	X		
50	Weindl et al. (2017b)	Y							Y					T	X		X	X	X			X		
51	Bahadur et al. (2018)	N				Y	Y							T	X	X	T							
52	Searchinger et al. (2018)	Y	Y	Y	Y	Y	Y							T	X	X	X	X	X	X	X	X	X	
53	Stevanovic et al. (2017)	Y	Y	Y	Y	Y	Y	Y						T	X	X	X	X	X	X	X			
54	Zhang et al. (2015)	N									Y			T	-		T	T				T	X	
55	FAO (2018)	Y	Y	Y		Y				Y		Y		T	X	X	X	X	X	X				
56	FOLU (2019)	Y	Y	Y	Y	Y	Y	Y						X	X	X	X	X	T	X	X			
57	Theurl et al. (2020)	Y	Y	Y	Y	Y	Y							T	V		X	X	X				X	
58	Clark et al. (2020)	Y	Y	Y	Y	Y								T	V	X	X	T	X	X				
59	Chang et al. (2021)	Y	Y	Y		Y	Y	Y		Y	Y			T	X	X	T	T	T	X			X	X
60	Beusen et al. (2022)	Y								Y	Y	Y	Y	X	X	X	X	T	T	X			X	X

* $P_{instream}$ is calculated from $P_{surplus}$ as described in Table S2.

Table S5. Minimum set of quantitative variables required to derive necessary predictors across all meta-regression models (see Section 1.4). For complete list of data and variables see Data S1. [FCR = feed conversion ratio, FCF = food-competing feed].

Intervention	Variables (#)	Variable names and description	Unit (s)
Population	1	Global population	Billion
Diet	6	Ruminant meat, other meat, seafood, dairy, eggs, plants	food supply (kcal/cap/day)
Waste	6	Ruminant meat, other meat, seafood, dairy, eggs, plants	% waste
Crop yields	1	Cereal yield (global average yield for all cereals)	t DM/ha
Feed efficiency	3	FCR (ruminant meat, monogastric meat, dairy)	kg DM/kg
Feed composition	3	FCF (ruminant meat, monogastric meat, dairy)	% for each livestock type
Climate action	3	CH_4 intensity, N_2O intensity, Carbon price	%Δ CH_4/N_2O, \$/tCO_2e
Water-use efficiency	1	Blue water consumption/water withdrawals	kg/m^3
N efficiency	1	Nutrient-use efficiency (outputs/inputs)	NUE (dimensionless)
P efficiency	1	Nutrient-use efficiency (outputs/inputs)	PUE (dimensionless)
N recycling	1	N inputs from recycled sewage & household waste	%
P recycling	1	P inputs from recycled sewage & household waste	%

1.3.3 Alternative food system sustainability narratives

Studies often combine interventions to create scenarios in a way that represents one or more of the prevailing sustainability worldviews (*23*, *107*). Some worldviews and even individual interventions (e.g., reduction in food loss and waste, disruptive technologies like novel proteins) may often combine demand- and supply- side elements (Table S6). Some studies intentionally focus on comparing scenarios that represent competing or complementary worldviews around food system sustainability (*23*, *107*, *108*). Even studies that adopt a similar worldview (e.g., sustainable intensification) may parameterise their scenarios and intervention levels very differently depending on the focus (e.g., the environmental indicators of interest) of the study.

Table S6. A summary of dominant food system sustainability narratives and associated combinations of supply- and demand- side interventions. Also presented are key studies and examples of on-ground actions/solutions and their most representative of the narratives.

Food system sustainability narrative	**Interventions**		**Supply chain stages impacted**	**Typical on-ground action example(s)**
	Supply-side	**Demand-side**		
Sustainable intensification (*109-111*)	- Yield gap closure - Feed efficiency - Nutrient-use efficiency - Water-use efficiency		Production to distribution	- Nitrification inhibitors - Digital or precision agriculture
Circular economy (*112-114*)	- Nutrient recycling - Feed composition (reduction in food-competing feed) - Waste/loss reuse reduction		Production to distribution	- Livestock raised on waste or by-products
Agroecology (*28, 112*)	- Organic production - Nutrient recycling - Ecological leftovers	Less but better meat Reduced waste	Production to consumption	- Crop rotations - Agro-forestry
Healthy and sustainable diets (*19, 64, 83*)		Reduction in animal protein Waste reduction Increased intake of fruits and vegetables	Retail and Consumption	- Taxes on ruminant meat - Education campaigns
Technological breakthroughs (*23, 113, 116*)	- Yield gap closure (novel crop breeds) - Feed conversion efficiency - Nutrient-use efficiency	Novel proteins for food and feed	Production to consumption	- Cellular meat - Bacterial protein
Degrowth (*108, 117*)	- Regenerative/organic production - Sufficiency	- Ethical consumption - Sufficiency	Production to consumption	- Fairer income redistribution

1.3.4 Gaps in intervention coverage across studies and planetary boundaries

As a result of complex narratives giving rise to integrated scenarios, the coverage of interventions across studies and different environmental indicators (and planetary boundaries) is highly heterogeneous (Table S7). A strong emphasis on diet change (72% of studies) and crop yields (68%) occurred across all studies. Feed efficiency (47%) and food waste reduction (38%) followed in terms of study coverage, although a considerable percentage of studies focusing on freshwater use and biogeochemical flows did not consider these interventions. Around 70% of studies across all boundaries did not explicitly model interventions associated with changes in feed composition and their interaction with feed efficiency (*118, 119*). Similarly, more than 72% of studies did not consider population estimates beyond BAU trends, an issue recently highlighted in (*103, 120*). There is also a low general coverage of resource-use efficiencies with the exception of biogeochemical flows where nutrient-use efficiency is a key intervention (*87*).

Table S7. Coverage of all identified interventions across planetary boundaries. Cells show the percentage (shades of blue for >50% and shades of orange for <50%) of studies covering a planetary boundary that contain scenarios where an intervention is explicitly considered (i.e., set at a level above or below the BAU level) as a mitigation action. For more details and indicator-specific results see T2 Data S1.

	Planetary boundaries → **Interventions ↓**	Climate change	Land-system change	Freshwater use	Biogeochemical flows	All boundaries
Demand-side	Population	13%	23%	29%	42%	28%
	Diet change	92%	79%	59%	79%	72%
	Waste reduction	67%	56%	29%	42%	38%
Supply-side	Crop yields	79%	82%	59%	67%	68%
	Feed efficiency (FCR)	63%	54%	18%	46%	47%
	Feed composition	38%	36%	12%	42%	30%
	Climate action *	79%	36%	18%	29%	33%
	Water-use efficiency	0%	0%	53%	0%	23%
	Nutrient-use efficiency	42%	0%	0%	71%	40%
	Nutrient recycling	21%	23%	12%	54%	25%
	# Studies	24	39	17	24	60
	% of reviewed studies	40%	65%	28%	40%	100%

* Climate action includes all actions that result in gains in the emission intensity of crops and livestock (e.g., livestock supplements, nitrification inhibitors, carbon price). FCR = feed conversion ratio.

1.4 Meta-regression modeling and risk assessment

1.4.1 Overview

The overall aim of the study was to statistically quantify the influence of individual and combined food system interventions on reducing the risk of exceeding environmental limits. To achieve this aim, we first developed meta-regression models for each of the 10 environmental indicators (see Section 1.2). The fitted meta-regression models were then used to create projections for all combinations of interventions across ambition levels (Section 1.4.2). The projections in physical units (e.g., Gt CO_2e) from the meta-regression models were subsequently compared to the PDFs representing each of the planetary boundaries identified during the systematic review process (Section 1.2) to compute the risk of exceeding each planetary boundary. Our analysis comprised the following steps:

1. We used our quantitative input database (Data S1) compiled from the studies selected in our systematic literature search (Section 1.1) and the insights gained from reviewing these studies and the wider literature to create a study-indicator-intervention matrix (Table S4) and a detailed table of actions (Data S3). These were then used as a basis to establish a set of key intervention strategies (Table S7) with the necessary underpinning quantitative variables to describe them (Table S5).
2. We fitted 9 independent linear mixed models (LMMs) for cropland, pasture, methane, nitrous oxide, blue water consumption, nitrogen fertilizer, nitrogen surplus, phosphorus fertilizer, and phosphorus surplus), with the log response ratio (*LnR*, logarithm of the ratio of *future prediction/base year prediction*) of each environmental indicator as the dependent variable. LnR is commonly used as the response variable in meta-regression analysis (*121-124*). For each LMM, we tested alternative random effects structures using random intercepts and also slopes for the main fixed effect predictors, and settled on the use of a simple random intercept model design with model ID as the random effect (*125, 126*). The exception were the meta-regression models for blue water consumption and nitrous oxide where a more complex random slope and random intercept were used to accommodate more strongly divergent model assumptions established during correspondence with study authors. Key predictors (calculated as per #1 above) were selected as fixed effects terms for each environmental indicator (Section 1.4.4). Relevant fixed-effects predictors for each meta-regression model were calculated as indices (% change relative to the base year) from this minimum set of quantitative variables, thus achieving a greater degree of harmonization across all studies.
3. Following best practice for selecting predictive models (*127, 128*), we carried out repeat K-fold cross-validation (*129*) of alternative random and fixed effect model structures ranging from the least parsimonious (all variables used as independent predictors), hybrid (selected aggregation of predictors e.g., per capita caloric demand estimates multiplied by population), and most parsimonious process-based (aggregates of independent predictors e.g., total feed demand by livestock type), and selected the model with the best prediction skill (with the lowest RMSE) for each environmental indicator.
4. Plausible levels of implementation settings ranging from low to very high mitigation ambition were then defined for each intervention strategy. We used the LMM with the highest predictive accuracy (lowest RMSE) to calculate make predictions for the average group using the mean of the distribution μ_{group} (*126*) along with associated prediction intervals using the 'predictInterval' function in *merTools* (*130*) for each

of the 9 indicators under all possible combinations of intervention levels for 2050. This resulted in a database of intervention combinations with internally consistent 2050 storylines across all indicators. Predictions were converted from LnR to % change using the formulae *100 * (exp(LnR) - 1)*, and then to physical units (Mha, Mt CO_2e, km^3, and Tg N/P) by multiplying the corresponding 2010 base year values (Table S25). To address the considerable variation in scope across land use change CO_2 emissions estimates in the reviewed studies (see Data S1), we used data from the AR6 Scenarios Database (*35*), to fit an additional LMM to estimate emissions associated with land-use change (see Section 2.2.2). The land-use change model was then used to predict emissions associated with land-use change for the same consistent 2050 storylines using the projections from the cropland and pasture models as inputs.

5. We calculated aggregated boundary distribution estimates for land-system change and climate change [total agricultural area = cropland + pasture, Total emissions = CH_4 + N_2O + CO_2 (LUC)] by adding together the means and variances from individual indicator prediction intervals, as per the normal sum theorem (*131*). We then computed the risk of exceeding environmental limits across the four planetary boundaries associated with each projection by combining uncertainty in LMM predictions and uncertainty in environmental limits as represented by each corresponding probability density function (Section 1.4.5). For water no further calculations were required since the freshwater use boundary is only represented by a single indicator. In the case of biogeochemical flows, we calculated risk estimates for each of the indicators (N_{fert}, $N_{surplus}$, P_{fert}, $P_{instream}$) as the distributions cannot be added together in the same way as for land-system change and climate change. We then calculated average risk metrics for N and P by combining all indicator risk estimates, and, finally, we combined averaged N and P estimates to calculate an aggregate risk metric for the entire biogeochemical flows boundary.

6. Based on risk estimates for all intervention combinations, we calculated average risk of exceedance and *risk difference* (an indication of risk mitigation potential for each intervention level, calculated as risk of exceedance at each level minus risk of exceedance at Trend level) for each intervention-level combination across each planetary boundary. We also carried out a similar calculation to estimate absolute change in physical units for each indicator (see Fig. S4, Fig. S5).

7. We finally mapped the performance of all intervention combinations against their risk mitigation and ambition level. We did this for each of the four planetary boundaries, and for all boundaries combined, yielding a total of 2,097,152 plausible intervention level combinations across all boundaries (Fig. S6). We then selected the scenarios that met two critical IPCC-calibrated uncertainty risk thresholds (36) across all boundaries: < 0.50 risk (exceedance *about as unlikely as not*) and < 0.33 risk (exceedance *unlikely*), and categorized them in terms of the type and level of each intervention required to achieve each threshold indicator.

1.4.2 Setting ambition levels for all intervention variables

Population

The total number of people on the planet in 2050 is a key determinant of aggregate food demand and associated environmental impact (*103*, *132*). While many of the studies reviewed held population constant across scenarios, they still used different projections for 2050 depending on their data sources and their date of publication. Other studies have used established storylines such as SRES, MA, and the SSPs, all of which include scenarios with significantly different population projections. More environmentally sustainable scenarios were generally associated with lower population growth (*132*, *133*). We selected a range of population levels to encompass various assumptions about key parameters likely to affect the extent of this intervention such as fertility, mortality, migration, and education centered around the 2019 United Nations Department of Economic and Social Affairs (UN DESA) medium population estimate for 2050 (*134*). We used the following 4 levels (in order of increasing mitigation ambition):

- Low (10.588 billion) – This high population estimate for 2050 corresponds to the 2019 UN DESA high fertility variant (*134*). It is higher than the ~10 billion that corresponds to average SSP3 estimates (*133*), reflecting a very low level of ambition in fertility trajectories.
- Trend (9.735 billion) – This corresponds to the 2019 UN DESA median (50 percent) prediction interval (*134*), reflecting the most likely trends in fertility, mortality, migration and education.
- High (8.907 billion) – This estimate corresponds to the low fertility variant from the 2019 UN DESA trajectory. This trajectory results in a slightly lower 2050 estimate compared to SSP2 (*133*). Several studies use a similar population estimate in variants of the SSP2 scenario (*31, 86, 135*).
- Very high (8.500 billion) – This corresponds to an average projection for the SSP1 scenario, used in several of the reviewed studies. It assumes a rapid acceleration of the demographic transition due to very high educational and health investments (*133, 136*).

Diet

In addition to population, aggregate demand for agricultural commodities is highly sensitive to assumptions around per capita dietary intake and diet composition. Changes in diets are a key demand-side mitigation strategy in global food system scenario studies, with several highly cited food system modeling studies published in the last decade focusing on the mitigation potential of healthy and sustainable diets (*19, 64, 76, 83*). Diet scenarios vary widely in their formulation across studies. Commonly modeled diets include:

- Omnivorous BAU – Diets containing all types of animal source foods (ASFs) in average proportions with no assumed substitution. This diet type is by far the most common in the reviewed studies and ranges from very high animal calorie consumption to very low animal calorie consumption such as flexitarian diets (*19, 64*).
- Substitution – Diets where ruminant meat is partially substituted with monogastric meat, most commonly by 10 – 20% (*31, 94, 137, 138*).
- Mediterranean – Diets rich in vegetables, fruit, seafood, grains, sugars, oils, eggs, dairy, and moderate amounts of meat (*83, 105*).
- Dairy-based – Diets containing a much higher than average percentage of dairy products, some of which are assumed to replace ruminant meat (*23, 64*).
- Pescatarian – Diets where animal protein is sourced predominantly from marine sources but still contain modest amounts of dairy/eggs (*23, 64, 83, 105*)

- No meat – Vegetarian diets containing no meat (*23, 64, 83, 84, 105, 139-141*) corresponding to vegetarian diets, or vegan diets with no animal calorie intake.

While a higher level of agricultural commodity detail was offered by some studies that distinguished between the many different animal and crop products consumed, many studies did not provide this level of detail (see Section 2.4.4 for discussion on aggregation bias). Here we used a combination of four continuous predictor variables to broadly define the global dietary change intervention in terms of food supply (intake plus waste at the household and retail level) (*142*). These estimates were either available in the reviewed literature, could be calculated using regional production estimates and assumptions related to waste, or calculated using production data in combination with FAOSTAT conversion factors for 2010 (*142*), with contribution of corresponding authors (Section 2.1, Data S1).

The modeled diet variants encompassed the plausible range in plant, ruminant meat, dairy, and non-ruminant calories (including eggs and aquaculture products) that could satisfy minimum nutrition requirements but also represent overconsumption across scenarios from the literature (*19, 76, 106*) (Data S1). The minimum caloric intake meets minimum dietary energy requirements for healthy populations with body mass index values between 18.5 and 24.9 (*19*), while values >2400 represent overconsumption (*143*). While not explicitly defined due to the use of only a single plant calorie predictor, we implicitly assume a healthy diversity in plant calories as defined in all underlying study scenarios used to fit the statistical models.

Given the critical role of ASF in supplying adequate dietary vitamin B_{12} (*144*), we also considered this dimension in the formulation of the diets. Assuming caloric shares of the 35 most commonly consumed animal products that reflect global average base year (2010) totals in the FAOSTAT Food Balance Sheets (*142*) along with nutrient content estimates from the USDA food composition database Standard Reference 28 (*145*), we also estimated total daily vitamin B_{12} availability of each ASF variant and compared this to recommended nutrient intakes. All ASF variants meet the World Health Organization 2.4 μg day^{-1} recommendation for adults and adolescents (*146*) but the Low ASF variant falls short of the European Commission's 4 μg day^{-1} recommendation (*147*), and suggests that this diet variant could require additional supplementation and fortification of plant foods to ensure adequate vitamin B_{12} intake.

To enable the consideration of reduced overconsumption, we model plant calories as a variable with four levels that covers the plausible range of 1860-2350 kcal cap^{-1} day^{-1} ensuring that all modeled diets, including the Low ASF + 1860 combination that corresponds to the flexitarian variant in the EAT-Lancet Commission (*64*), contain sufficient plant calories. We did not consider diets with zero meat or animal calorie intake due to their lower feasibility.

Table S8. Calorie sources under four modelled diets combining assumptions around animal and plant calorie intakes. (ASF = animal-sourced foods).

ASF variant	Diet pattern	Ruminant	Monogastric	Dairy	Animal total	Plant total	Grand total
Rich	Rich + 2350	65	320	170	555	2350	2905
BAU	BAU + 2350	50	260	150	460	2350	2810
Low meat	Low meat + 2350	40	230	160	430	2350	2780
Low ASF	Low ASF + 2350	25	145	115	285	2350	2635
Rich	Rich + 2185	65	320	170	555	2185	2740
BAU	BAU + 2185	50	260	150	460	2185	2645
Low meat	Low meat + 2185	40	230	160	430	2185	2615
Low ASF	Low ASF + 2185	25	145	115	285	2185	2470
Rich	Rich + 2020	65	320	170	555	2020	2575
BAU	BAU + 2020	50	260	150	460	2020	2480
Low meat	Low meat + 2020	40	230	160	430	2020	2450
Low ASF	Low ASF + 2020	25	145	115	285	2020	2305
Rich	Rich + 1860	65	320	170	555	1860	2415
BAU	BAU + 1860	50	260	150	460	1860	2320
Low meat	Low meat + 1860	40	230	160	430	1860	2290
Low ASF	Low ASF + 1860	25	145	115	285	1860	2145

Table S9. Estimates of total daily vitamin B_{12} supplied by each ASF diet variant compared to international recommendations for adults. (WHO/FAO = World Health Organization/Food and Agriculture Organization. EC = European Commission).

ASF variant	Total daily vitamin B_{12} (μg day^{-1})	Meets WHO/FAO requirement (2.4 μg day^{-1})	Meets EC requirement (4.0 μg day^{-1})
Rich	5.76	Yes	Yes
BAU	4.74	Yes	Yes
Low meat	4.35	Yes	Yes
Low ASF	2.85	Yes	No

We modeled the following ASF variants:

- Rich – A global dietary pattern representative of scenarios that assumes levels of animal product demand (consumption) increasing beyond projected trends (*15, 107*). This pattern corresponds to current diets with a high share of calories from ASF such as those consumed in many developed countries (*135, 148-150*).
- BAU – This pattern assumes increased consumption in ASF in line with past and current trends consistent with BAU diets in the database (Data S1) of reviewed studies (*15, 19, 64, 83, 107*). This assumed ASF intake is representative of a nutrition transition (*151*) towards more affluent diets with higher shares of ASF compared to the current global average.
- Low meat – This diet patterns is representative of some SSP1 scenarios (*24, 152*), as well as other scenarios which assume more healthy and sustainable diets with reductions in ASF (*76, 107, 135, 153, 154*). This ASF pattern is also potentially representative of pescatarian or Mediterranean diets which are also commonly

associated with reduced animal calorie intakes compared to a BAU diet (*64, 83, 105*).

- Low ASF – The highest possible mitigation levels modeled in our database in terms of diet change, compatible with the flexitarian diet variants proposed by the EAT-Lancet Commission (*19, 86*). Other studies also model healthy and sustainable diets with a similar ASF profile (*40, 46*) that roughly corresponds to a halving (-50%) of current meat consumption while maintaining a modest intake of dairy.

Waste reduction

Food loss and waste are a major source of environmental impact, with current global estimates of around one-third of food produced being wasted (*155*). Significant reductions in food loss and waste are embedded in the SDGs. SDG 12 specifically recommends halving food waste relative to present levels by 2030, a possibility commonly modelled by authors in waste mitigation scenarios for 2050 (*19, 23, 46, 76*). Recent studies argue that such targets present a major challenge, with expectations that waste may increase under a BAU trajectory due to higher incomes and reduced food prices in major developing economies (*156*).

Most studies (including all of those reviewed here) consider waste (and loss) as part of the aggregate demand for food commodities. Waste reduction is therefore modeled as a reduction in aggregate demand (at varying rates depending on the perishability of each food commodity and the magnitude of the assumed reduction). This then translates into a direct reduction in the amount that needs to be produced, with environmental benefits accruing due to forgone production. While we acknowledge that a direct reduction in food waste may not necessarily result in concomitant reductions in production due to price changes and rebound effects (*157*), we follow the same convention as in the reviewed studies by modeling change in waste as a change in aggregate demand.

As in most reviewed studies, we focus on the food waste portion, as this is more directly related to consumption-based food waste reduction interventions achieved through actions at the retail, food service and household level (*158, 159*). Food supply, as reported in the FAOSTAT Food Balance Sheets (*151*), refers to the food which is available food available for consumption at the retail level, and is therefore inclusive of household and retail food waste. Waste reduction (or change) is therefore modeled as a reduction in total food supply (per capita supply multiplied by population). Estimates from few studies reporting food consumption exclusive of waste were adjusted for waste based on data obtained directly from the authors and from FAOSTAT (*155*) (Section 2.1, Data S1).

Here we modeled waste implications via a reduction/increase in required food supply to meet each of the diet variants, based on weighted global average waste percentages from (*19, 155*) for each commodity category. The underlying assumption is that we implicitly assume that the composition of plant foods and non-ruminant protein consumed does not change significantly compared to the base year. While this could introduce some error when modelling potential shifts to diets with a higher percentage of perishable items such as seafood and fresh fruit and vegetables, this assumption is necessary and justified by the degree of commodity aggregation used in our diet variants.

Table S10. Per capita food supply (kcal person^{-1} day^{-1}) across diet-waste scenario combinations. Waste fractions calculated as weighted averages from data sourced from (*19*).

Diet	Category	Current waste	Current supply	BAU-High	BAU-Low	Half	Intake
Rich	Dairy	5.7%	180	183	177	175	170
Rich	Non-ruminant	12.0%	360	371	349	338	317
Rich	Ruminant meat	7.9%	70	71	69	67	64
Rich	Plant	19.1%	2300	2410	2190	2080	1860
Rich	Plant	19.1%	2500	2619	2381	2261	2022
Rich	Plant	19.1%	2700	2829	2571	2442	2184
Rich	Plant	19.1%	2900	3039	2761	2623	2346
BAU	Dairy	5.7%	160	162	158	155	151
BAU	Non-ruminant	12.0%	295	304	286	277	260
BAU	Ruminant meat	7.9%	55	56	54	53	51
BAU	Plant	19.1%	2300	2410	2190	2080	1860
BAU	Plant	19.1%	2500	2619	2381	2261	2022
BAU	Plant	19.1%	2700	2829	2571	2442	2184
BAU	Plant	19.1%	2900	3039	2761	2623	2346
Low Meat	Dairy	5.7%	160	162	158	155	151
Low Meat	Non-ruminant	12.0%	230	237	223	216	202
Low Meat	Ruminant meat	7.9%	40	41	39	38	37
Low Meat	Plant	19.1%	2300	2410	2190	2080	1860
Low Meat	Plant	19.1%	2700	2829	2571	2442	2184
Low Meat	Plant	19.1%	2900	3039	2761	2623	2346
Low Meat	Plant	19.1%	2500	2619	2381	2261	2022
Low ASF	Dairy	5.7%	120	122	118	117	113
Low ASF	Non-ruminant	12.0%	165	170	160	155	145
Low ASF	Ruminant meat	7.9%	25	25	25	24	23
Low ASF	Plant	19.1%	2300	2410	2190	2080	1860
Low ASF	Plant	19.1%	2900	3039	2761	2623	2346
Low ASF	Plant	19.1%	2500	2619	2381	2261	2022
Low ASF	Plant	19.1%	2700	2829	2571	2442	2184

Crop yields

Interventions involving increases in crop yields that result in yield gap closure are one of the most common manifestations of improved productivity in the agricultural system (*160, 161*) and thus feature prominently in the reviewed studies (Table S7). A number of actions ranging from plant breeding to create higher-yielding crop varieties, improved fertilization and/or irrigation (e.g. through precision technologies), and agronomic practices optimized to the local context, can all boost yields (*160*). Studies often refer to the yield gap, defined as the difference between the observed crop yield and the crop's maximum attainable (potential) yield in a particular location given optimal agricultural practices and technologies (*160, 162-164*). A challenge encountered in harmonizing yield data across different studies was that some studies reported actual crop yield in tonnes of dry matter per hectare (t DM ha^{-1}), while others report the percentage increase (simple or compound over the period between the baseline and 2050), the extent of yield gap closure (%), or yield gap closure relative to the present or a past base year (%). Several reference or worst-case scenarios also assume that yields stagnate (remain constant) at base year levels (Data S1).

In our analysis, we have addressed the issue of different yield metrics by sourcing the original crop yield data in t DM ha^{-1}. We then carried out any necessary aggregation to calculate global weighted average cereal yields. We focused on cereal yields as a proxy for yields since cereals account for most crop production for food and feed and are better researched, with several studies concentrating on major cereals as a proxy for overall yields (*15, 165, 166*). Other crop yields are also available in the database (see Data S1) for most studies but these were not used in the training of the models. In accordance with our general approach, to ensure better harmonization between studies with different base years, we use percentage change relative to the base year as the predictor variable instead of the alternative of harmonizing yield estimates relative to a 2010 base year based on timeseries of global average cereal yields from FAOSTAT (*167*). We selected this approach following comparisons with FAOSTAT yield data and discussions with study authors. It also allowed us to include studies (*40, 105*) that assumed aggregate crop yield increases across all crops including cereals, studies (*31, 83*) that assumed cereal yield increases expressed in caloric (kcal ha^{-1}) terms, and all studies (*75, 86, 135, 153*) that use the MAgPIE model in which yields are calculated endogenously on the basis of a technological change rate (*168*).

To capture the reported range in yields in the reviewed studies and to encompass the diverse impacts of different productivity assumptions and climate change impacts on yields, we modelled the following four levels of crop yield increase by 2050 relative to the 2010 base year:

- Low (15%) – Yields increase relative to their present level but at half the rate of the historical average of 30% that would be expected by 2050 as per (*15*). This represents a worst-case-scenario that could also be considered as indicative of potentially negative impacts of climate change on crop yields (*28, 29, 169*).
- Trend (30%) – Yields follow a BAU trajectory. Calculations based on data in the reviewed studies (T1 in Data S1) and (*166*) established a range of 25% to 35% increase in yields across most BAU scenarios.
- High (45%) – Yields increase at a rate 50% higher than the most commonly specified BAU trajectory. Calculations based on data in the reviewed studies (Data S1) established an increase in yields of around 40 to 50%, corresponding to a *high* yield increase across most major studies (*56, 83, 94, 132*). This also aligns with assumptions under the SSP 1 storyline (*152, 166*) and a 90% yield gap closure for major cereals (*160*).
- Very high (60%) – Yields increase is highly ambitious at double the BAU trajectory and is representative of optimistic yield gap closure scenarios (*19, 64, 76, 166*), corresponding to a 100% yield gap closure for most major cereals (*160*).

Feed efficiency (feed conversion ratio)

One of the largest contributors to the higher volumes of global food production alongside crop yields in recent decades has been the significant gains in livestock productivity (*15*). Past increases in livestock productivity have been driven largely by scientific and technological developments in breeding, nutrition and animal health, and this trend is expected to continue in the future, particularly in developing countries where the current productivity gap remains high (*170, 171*). The reviewed studies use several different metrics to describe livestock productivity. This partly relates to the fact that each system of animal production (e.g., feedlot, rangelands, grass-fed, mixed crop-livestock) has different inputs and efficiency levers (*172*), and productivity can therefore be measured in a number of different ways.

The most frequently reported indicators of livestock productivity are feed efficiency (i.e., the ratio of outputs to inputs, e.g. kg of animal product/protein per kg of feed in DM, or also reported as Joules of animal product per Joule of feed) and its inverse, the feed conversion ratio (FCR), which is the ratio of inputs to outputs, e.g. kg DM per kg of animal product/protein. The feed efficiency of different livestock commodities ranges widely both between different animal and commodities but also for the same commodity produced under different farming systems (*23*, *118*, *137*, *152*).

In addition to improved feeding and feed-use efficiency, a number of other livestock efficiency variables such as improved feed digestibility, protein, and mineral contents achieved through changes in feed composition or feed additives; breeding, and; herd management (*29*, *94*, *173*) also significantly impact overall livestock productivity. Pasture productivity can also be a key metric for grass-fed ruminants (*83*). Stocking density (i.e., head of stock per unit area) is also used as a relevant metric for livestock fed on pasture (*76*). Some studies refer to separate livestock productivity gaps for ruminants and monogastrics expressed as a percentage in a similar way as for crop yield gaps (*135*). The relative importance of different feed efficiency variables also depends on the environmental indicator of interest. For instance, feed additives that reduce enteric fermentation in ruminant livestock may significantly reduce GHG emissions (*19*, *132*, *174*), but this will not necessarily reduce resource use (i.e., land, water, nutrients) if feed efficiency remains unchanged or feeding levels increase (*174*). Similarly, N and P excretion could be reduced by changing feed composition through increasing the use of concentrates or by increasing N conversion rates (*94*). However, this could result in increased cropland and/or water requirements. Another commonly used metric of livestock productivity that is especially important in terms of GHG emissions is yield per animal, is explicitly considered in a few of the reviewed studies employing assumptions (*28*, *75*, *135*, *153*).

Unlike crop yields where a weighted global average yield index serves as an all-encompassing proxy, adequately capturing feed efficiency ideally requires multiple separate livestock productivity-related indicators for each major livestock commodity. Following an audit of all studies and the available data, we determined that the FCR, expressed as kg DM per kg of animal product, was the most ubiquitous metric of feed efficiency. As with crop yields, we sourced the original FCR data for each livestock commodity considered in each study and we harmonized this to match our ASF categories (see *Diet*) by calculating a weighted global average FCR across three livestock types: ruminant meat (beef, goat and mutton), dairy, monogastric products (pork, poultry, eggs and seafood). Similarly to crop yields, our use of percentage change relative to the base year as the predictor variable also allowed the inclusion of studies that considered only the crop portion of livestock feed intake (*19*, *64*), studies that used a protein conversion ratio(*83*), and studies where feed efficiency was approximated by an index of livestock productivity (*28*, *107*).

Table S11 summarizes the ambition levels related to this intervention and the assumptions underlying those choices for each of the livestock categories. To control for the fact that studies can have different base year FCRs depending on the sources they use, as with all predictors in the models, we model all changes as percentage change relative to our assumed base year values, which correspond to the Low setting (see Table S11), with the Very High setting representing a ~40% reduction in FCRs across livestock categories.

Table S11. Feed conversion ratio scenario assumptions across each of the three livestock categories for 2050. The assumed range is drawn from data in the reviewed studies (see Data S1).

Livestock category	Low	Trend	High	Very High	Justification
Ruminant meat	35	30	25	20	The assumed range spans the current global average (*152*) to highly efficient but predominantly grassfed dominated systems such as those in Australia and New Zealand (*175*). The High setting represents SSP1 scenarios (*152*). While some grain-dominated systems (*40, 150*) or dairy systems were meat is a by-product (*23*) can achieve FCRs much lower than 20, we did not consider these values to ensure compatibility with our feed composition storylines and assumptions. The scenarios are based primarily on beef cattle as opposed to smaller ruminants (e.g., sheep and goats), since beef accounts for ~80% of the caloric and mass share of ruminant meat in global diets (*142*).
Dairy	2	1.75	1.5	1.25	The assumed range spans the current global average (*176*) to that already achieved in efficient but predominantly grassfed systems such as those in Australia and New Zealand or western Europe (*137*). Similarly to ruminant meat, highly efficient systems can achieve FCRs closer to 1 (or below) is some cases (*152, 175*), but such FCRs are more representative of grain-dominated systems (*150*). The Trend setting represents an average of BAU scenarios across studies assuming mixed production systems (*42, 46*), while the High setting assumes continued intensification as per SSP1 or other moderate efficiency scenarios (*23, 40, 132*).
Monogastric	4	3.5	3.0	2.5	The Low setting is representative of the current global weighted average for monogastric meat dominated by pork and poultry (*142*), in addition to eggs, and aquaculture products in industrial production systems (*23, 40*). The Trend and High settings assume further global intensification and reductions in FCRs consistent with SSP2 and SSP1 trends respectively. The Very High setting assumes universal adoption of highly productive intensive systems (*23, 132*). It also potentially accommodates a higher share of aquaculture products human diets. Most aquaculture products have average FCRs below 2 with commonly eaten species such as salmon and tilapia being closer to 1 (*177*). An increased percentage of calories from aquaculture products consistent with pescatarian or frequently modelled flexitarian diets such as the EAT-Lancet (*64*), would therefore result in a reduced FCR for monogastric products.

Feed composition

In addition to the FCR, another important and closely related parameter of livestock production with significant environmental implications is the composition of feed. Several recent studies (*23, 28, 29, 114, 119, 178*) highlight the potential environmental benefits associated with reducing the proportion of human-edible biomass (e.g., cereal crops) termed *food-competing feed* (FCF) (*29*) consumed by livestock and increasing the proportion of ecological leftovers (i.e., grass, waste, by-products) or low-opportunity-cost biomass (*179*) in livestock diets. A continuation of the recent historical trend towards higher demand for animal calories and more intensive livestock production with higher feed efficiencies is typically associated with an increased proportion of FCF under most BAU scenarios (*76*). Most reviewed studies (Data S1) make implicit assumptions around feedlot intensification with a higher contribution of FCF across scenarios with higher feed efficiency (i.e., lower FCRs) (*135, 153*). On the other hand, several studies (*23, 28, 29, 94, 150, 180, 181*) explicitly modelled scenarios with reduced FCF and higher proportions of grass and by-products as representative of circular economy and agroecology sustainability narratives (Table S6).

Our choice of livestock categories was also motivated by the fact that feed composition for ruminant meat, dairy and monogastric products is, on average, distinctly different. As with FCR, we therefore control for this by using three different percentages of FCF that accompany each of the three FCRs (Table S11) to model the effect of this intervention strategy on all indicators related to resource use (i.e., land, water, nutrients) and emissions (GHGs). FCF percentages were either sourced directly from authors or calculated based on detailed feed composition data where available. In order to harmonize the figures across studies, we distinguished between FCF estimates that had accounted for the use of residues and by-products (*23*, *28*, *29*, *105*) and those who did not, as several studies (*40*, *46*, *105*) only distinguished between grass and non-grass feed crops. Where the feed composition data did not explicitly quantify the use of residues and by-products, we used disaggregated data for 74 crops from FAOSTAT Commodity Balances - Crops Primary Equivalent (*182*) in addition to the classification of residues and by-products as per (*28*, *29*), to calculate a base year (2010) FCF percentage across all crops (*107*). Based on these calculations, we adopted a value of 93.6% (see T9, Data S1) as an adjustment factor for those studies that did not explicitly account for residues and by-products.

For ruminant meat and monogastric products, additional aggregation was necessary so we calculated these as the weighted mean percentage of total FCF by weight (in kg or tons of dry matter) relative to total feed intake (including grass and by-products), as follows:

$$FCF_r = \frac{\sum_{r=1}^{n} FCF_r * (FCR_r * P_r)}{\sum_{r=1}^{n} FCR_r * P_r} \quad \text{(Eq. S1)}$$

$$FCF_m = \frac{\sum_{m=1}^{n} FCF_m * (FCR_m * P_m)}{\sum_{m=1}^{n} FCR_m * P_m} \quad \text{(Eq. S2)}$$

where *r* are ruminant meats (beef, mutton and goat), and *m* are monogastric products (chicken, pork, eggs, and aquaculture), *FCF* is the percentage of feed from crops in direct competition with food, *FCR* is the feed conversion ratio, and *P* denotes the production quantity in kg tonne^{-1} of product *r* or *m*, respectively.

Both an increase or a reduction in FCF could be considered an intervention depending on the scenario narrative (Table S6). To ensure compatibility with BAU trends towards livestock intensification and higher FCRs (Table S11), we consider higher levels of ambition to correlate with higher percentages of FCF. However, we still ensure that our chosen levels allow FCF and FCR settings that remain realistic based on the plausible range in the reviewed data (Data S1).

Table S12. Food-competing feed settings across each of the three livestock categories for 2050. The assumed range is drawn from data in the reviewed studies (see Data S1).

Livestock category	Low	Trend	High	Very High	Justification
Ruminant meat	5	10	15	20	The assumed range spans the current global weighted average for beef cattle and small ruminants towards production systems with significant FCF percentages such as

Livestock category	Low	Trend	High	Very High	Justification
					those in North America (*118*). The Trend setting assume intensification following trends consistent with SSP2 scenarios (*135, 153*), while the High and Very High settings are typical of the degree of intensification seen in SSP1 scenarios (*92, 152*). Some predominantly grass-fed production systems such as in Australia and New Zealand can achieve Very High FCRs at the Low FCR setting (*175*).
Dairy	15	20	25	30	The assumed range spans the current global weighted average for dairy cattle towards production systems with significant FCF percentages such as those in North America (*118*). The Trend setting represents an average of BAU scenarios across studies assuming mixed production systems (*28, 46, 132, 135, 153*), while the High or Very High setting assumes significant intensification as per SSP1 (*152*), or other high productivity scenarios (*23*). Similarly to ruminant meat, highly productive grass-based systems such as in Australia and New Zealand can achieve Very High FCRs at the Low FCR setting (*175*).
Monogastric	80	85	90	95	The Low setting is representative of production systems with high percentages of residues and fodder typical of developing countries (*176*), or more circular systems (*23*). The Trend and High settings assume further global intensification and increases in FCFs consistent with BAU/SSP2 (*135, 153*) and high productivity/SSP1 (*23*) trends respectively. The Very High setting assumes almost 100% crop-based feed as seen in highly productive industrialised systems (*23, 105*). The assumed range resulting from all combinations between FCR and FCF accommodates for different shares of monogastric products (pork and chicken, eggs, and aquaculture), in addition to varying levels of productivity and degree of circularity and use of by-products in the system.

Climate action (emissions intensity and land-use mitigation)

Effective GHG mitigation across the food system requires a broad range of interventions such as technical options targeting non-CO_2 emissions reduction from crop and livestock production (*77, 183-185*), in addition to CO_2 savings related to energy and transport in the food supply chain both upstream and downstream (*78, 105, 186*), and concerted global efforts to eliminate cropland and pasture expansion and maximize land-based GHG sequestration (*187-189*). This intervention specifically concerns reductions in direct GHG emissions (CH_4, N_2O, CO_2 LUC) at the production stage beyond those associated with demand-side interventions (diet change and/or waste reduction) or productivity improvements already captured by other supply-side interventions such as crop yields, feed conversion ratios and feed composition. They specifically involve complementary technologies and mitigation actions (see Data S4 and detailed reviews in *73, 74, 190*), that reduce the non-CO_2 emissions intensity (emissions per unit of food produced) of crop and livestock production. Influential actions include feed supplements that reduce enteric fermentation in ruminant livestock (*174, 191*), improved manure management and infrastructure (*192*), improved nutrient and residue management in crop production and rice paddies, where practices such as alternate wetting and drying and careful selection of rice varieties can significantly reduce CH_4 emissions (*183, 186*).

A global carbon price provides an established mechanism to incentivize reductions in non-CO_2 emissions intensity while also reducing net CO_2 emissions from land use by reducing land clearing and promoting sequestration through trees and soil enhancement (*73*). Several of the reviewed studies (*75, 152, 193, 194*) explicitly considered the influence of a carbon price on climate change mitigation relative to a future baseline, most commonly calculated using the cost of GHG mitigation derived from non-CO_2 marginal abatement cost curves (MACCs) (*183, 186*). However, most studies did not directly incorporate a carbon price, with only five of the selected studies (*75*, *132*, *152*, *153*, *194*) modelling ecosystem conservation and restoration efforts such as payments for ecosystem services (e.g., REDD). Many studies and scenarios assumed either constant GHG intensities into the future (e.g., *28, 83, 165*), or considered potential GHG intensity reductions based on either past trends (*84, 105*) or mitigation potentials from the literature associated with technological advances or improved management (*19, 23, 40, 132*). While most studies assumed simultaneous (but often different) intensity reductions for both CH_4 and N_2O, a few studies (*42, 46*, *150*) only concentrate on N_2O intensity reductions arising from increased nutrient-use efficiency.

To adequately model the impacts of this intervention across all three GHG indicators (CH_4, N_2O, CO_2 LUC) in a way that also encompasses all the information from across the reviewed studies (Data S1), we used three separate metrics: CH_4 intensity (expressed as percentage change in CH_4 emissions per unit of food produced relative to 2010), N_2O intensity (expressed as percentage change in N_2O emissions per unit of food produced relative to 2010), and a harmonized carbon price in \$/tCO_2eq (in 2010 USD) as an established predictor of mitigation ambition for CO_2 LUC mitigation consistent with the IPCC AR6 database (*35*). Where CH_4 and N_2O emissions intensity was not explicitly provided in the study supplementary data (*19*, *40*, *64*), we calculated percentage change in emissions intensities by comparing emissions across relevant CH_4 and N_2O sources between scenarios with identical food supply that only differed in terms of GHG intensity, in order to control for the influence of other factors already encompassed in other interventions such as diet, waste, crop yields and feed efficiency and composition. While our statistical approach did not explicitly quantify complex interactions between nitrogen-use efficiency, feed efficiency, feed composition and non-CO_2 emissions intensity (due to changes in enteric fermentation and manure CH_4 and N_2O) that could occur due to changes in feed digestibility (*174*), the assumed mitigation levels are meant to, at least partly, encompass such interactions.

In selecting different mitigation ambition levels for CH_4 and N_2O intensities we have also considered their broad compatibility with carbon price assumptions based on studies (*75, 152*) that have explicitly modeled non-CO_2 mitigation associated with different carbon prices to ensure that there is consistency between the assumed ambition levels. While several studies assume comparable mitigation opportunities for CH_4 and N_2O, we take into consideration the fact that N_2O intensity reduction potential is considerably smaller compared to that for CH_4 according to studies employing MACCs (*75, 152*).

The following predictor levels were used (% applies only to CH_4/N_2O intensities, carbon price in 2010 USD applies to CO_2 LUC emissions):

- Low (0/0%, 0 \$ t CO_2^{-1}) – GHG intensities remain constant at base year levels assuming no changes in technology or farming practices (e.g., *28, 83, 165*), and there are no active efforts to curtail LUC emissions.
- Trend (13/4%, 25 \$ t CO_2^{-1}) – 13/4% reduction in in CH_4/N_2O intensities represents an average mid-point for BAU scenarios from (*84*, *105*, *195*). The carbon price corresponds to a BAU mitigation effort in terms of LUC emissions that corresponds to SSP2 (*75*, *152*).
- High (26/8%, 100 \$ t CO_2^{-1}) – 26/8% reduction in CH_4/N_2O intensities represents an ambitious improvement well above past efficiency trends (*105*). This percentage is also consistent with a high mitigation scenario for livestock in (*107*, *191*) that assumes that the emissions of the 10th percentile of the lowest-emitting countries in

the base year could be reached by other countries by 2050. For LUC, the carbon price corresponds to a coordinated mitigation effort that is considerably more ambitious than BAU and assumes a concerted but feasible and cost-effective global mitigation effort between 2020 and 2050 (*75, 132, 190*).

- Very high (40/12%, 200 \$ t CO_2^{-1}) – At around two to three times the rate estimated from the highest BAU trend (*105*) and comparable to the highest assumed intensity reductions assumes across studies for CH_4 (*40, 132*, *152*), a 40/12% reduction in CH_4/N_2O intensities from 2010 to 2050 represents an ambitious intensity reduction but one that is still well within technical constraints (*73, 183, 186*, *196*). For LUC emission mitigation efforts, 200 \$ t CO_2^{-1} corresponds to scenarios with stringent land-use change regulation and ambitious global sequestration efforts that remain feasible in terms of cost of implementation by 2050 (*73, 190*).

Water-use efficiency

As the most significant water user, accounting for ~88% of global blue water consumption from 1996 to 2005 (*197*), and given the anticipated increase in food demand, agriculture exerts significant pressure on the freshwater use boundary (*13, 65*). Boosting water-use efficiency (WUE) through improvements in technology and agricultural practices that enable reductions in runoff, soil evaporation, and drainage could optimize the amount of water retained in soils and available for plant growth (*198*). There is currently significant potential to increase WUE in agriculture, with most water-related studies in our dataset making projections of increased WUE as a key intervention strategy, although the best policies to enable such improvements are still under debate due to concerns around potential unintended consequences and management challenges associated with increase efficiency (*199*).

WUE is an important factor in the sustainability of water resources and environmental flows and is a major component of SDG 6, with Target 6.4 specifying the need to substantially increase WUE across all sectors by 2030 (*200, 201*). However, several WUE metrics expressed in different units are used across studies. The most common definition for WUE in the irrigation literature, also commonly referred to as *water productivity* (*164*, *199*), is the ratio of crop yield (or biophysical crop production) to the volume of water consumed (‘crop per drop’) (*199*). This definition, which also corresponds to the inverse of the blue water footprint (*197*) that is expressed in m^3/kg, is more consistent with the general notion of process efficiency which considers the ratio between the obtained product (the numerator) and the energy or resource invested in the process (denominator) (*202*). Another commonly used WUE metric in the reviewed literature is *field irrigation efficiency*, defined as the ratio between crop water requirements (i.e., consumptive blue water use) and irrigation water withdrawals (*15, 199, 203*), with several reviewed studies reporting this metric. Some studies (*105*, *152*) also used area-based metrics such as irrigated area unit of production as a proxy for WUE. Finally, WUE can also be expressed as the economic value added (e.g., in USD) per unit volume of water withdrawn across water-using sectors (i.e., agriculture, industry, households) (*204*).

We selected water productivity (i.e., ratio of crop yield to the volume of water consumed) as our default WUE metric. While most reviewed water studies (*61, 135, 164, 205*) directly reported or provided information (water consumption and water withdrawals) that could be used to calculate field irrigation efficiency, the required data for calculating water productivity was not readily available. We therefore carried out additional calculations to ensure that our selected WUE metric was available across all water studies as well as to control for the significant spatial variation in crop production across scenarios that gives rise to differences in total water consumption due to high variability in regional WUEs across agricultural sectors (*206*). For each study we calculated base year global weighted average blue water footprints (in m^3/kg) for each agricultural commodity (the level of commodity resolution varied across studies) and then multiplied these static commodity footprints by the total production amount in tons for each commodity in order to simulate total water consumption assuming base year productivities for each future scenario (see Eq. S3). To further harmonize across studies, we then compared the simulated water consumption with base year productivities to the actual water consumption of each scenario to estimate the percentage change in WUE relative to the base year for each future scenario, as per Eq. S4.

$$SWC_s = \sum_{c=1}^{n} \frac{BWC_{bc}}{P_{bc}} * P_{sc} \qquad \text{(Eq. S3)}$$

$$WUE_s = [1 - (AWC_s - SWC_s)] * 100 \qquad \text{(Eq. S4)}$$

where SWC stands for static water consumption (assuming base year water footprints), BWC is global blue water consumption by commodity (in m^3), P is the global commodity production (in tons), and AWC is the actual water consumption as per the published results reported by study authors. The indices *s*, *b* and *c* denote scenario, base year and commodity. For studies with scenario variants with identical food supply, we calculated WUE in a similar way to the process outlined above for Climate action, i.e. by comparing total (as opposed to commodity-specific) blue water consumption between scenarios with identical food supply that only differed in terms of GHG intensity, in order to control for the influence of other factors already encompassed in other interventions such as diet, waste, crop yields and feed efficiency and composition.

Study base years were all in the 2000-2010 range which ensured consistency given that it is broadly accepted that improvements in WUE at the global level were limited during this period (*15*). While virtual water trade (*207*) is not explicitly modeled as an intervention (see Section 1.4.3), the assumed intervention levels could be considered to incorporate the water-saving potential of concentrating production to more water-efficient locations (*206*, *208*). In some scenarios (*149*) the reallocation of global production to cater for increased regional populations in combination with self-sufficiency requirements led to reductions in global WUE. Similarly, the selected WUE metric considers all production (rainfed and irrigated) and therefore also implicitly controls for assumptions around the efficiency or extent of rainfed production that is another strategy that features in several scenarios (*60*, *135*, *164*, *205*). For two of the studies (*164*, *205*), WUE calculations were based solely on changes in cereal production as this was consistent with the analysis.

The following predictor levels were used:

a) Low (0%) – WUE remains constant at baseline levels. This setting reflects several studies or scenarios that did not make any assumptions with respect to WUE improvements (*28*, *29*, *31*, *149*) into the future.

- Trend (15%) – We took the efficiency increase estimate from (*164*) as indicative of a BAU improvement in irrigated areas, as has been adopted in several studies (see above) or can also be indicative of rainfed or pasture expansion scenarios (*205*)

- High (30%) – WUE increases at twice the BAU rate. This level of increase corresponds to that assumed in SSP1 scenarios (*61, 152*) and in Tech+ scenarios in (*19, 64*).
- Very high (45%) – This rate of increase is three times the BAU rate and corresponds to a highly optimistic global effort to improve WUE in agriculture. According to (*201*), to maintain or even reduce the global population suffering from water scarcity by 2050 and beyond, WUE needs to improve by more than 20-50% globally. We use a value of 30% which is within this range while also corresponding to the highest WUE increases (*60, 105*) in our database.

Nutrient-use efficiency

Nutrient-use efficiency for nitrogen (NUE_N) and for phosphorus (NUE_P) is defined as the percentage of nutrient inputs (organic + inorganic) harvested as product (*87, 88*). It is a key indicator of fertilizer application efficiency as it determines the fraction of applied fertilizer that is directly used by crops to grow versus that which is lost to the atmosphere, soils, and waterways through different biogeochemical processes (*92*). Future increases in food production from highly productive agricultural systems are expected to exacerbate nutrient-related environmental issues. Increased NUE is therefore likely to be one of the most effective means of increasing yields and food production while limiting environmental degradation (*87, 88, 201*).

Several alternative metrics are used across studies. The most common definition is a unitless ratio of outputs to inputs (i.e., NUE = total nutrient output / total nutrient input) (*209*). However, the concepts of apparent fertilizer use efficiency or partial factor productivity which represent the production in kg dry matter per kg of N or P fertilizer are also frequently used (*15, 210*). Other indicators such as soil N uptake efficiency (*86, 211*) and fertilizer efficiency gain (*141, 212*) are also used as a measure for NUE in some models. Irrespective of metric, NUE_N and NUE_P are subject to different processes and vary significantly between countries as a result of strong differences in crop mix and varieties, attainable yield potential, soil types, rates of application, and both past and current nutrient management practices (*46, 88, 210*). Hence, we included NUE_N and NUE_P as two distinct predictor variables in the N (N_{fert} and $N_{surplus}$) and P (P_{fert} and $P_{surplus}$) statistical models respectively.

As in the case of previous interventions, we harmonized the different metrics presented in the reviewed studies by calculating NUE as the established unitless ratio of outputs/inputs (as defined above), based on supplementary data supplied by authors on nutrient surplus and uptake in agriculture. To maximize compatibility across reviewed studies, we used NUE for the soil nutrient budget of the agricultural system (cropland and grassland) as opposed to whole-system or full-chain efficiency (*46, 88, 210*). In two cases where this metric could not be calculated due to a lack of available data (*76, 105*), scenarios with underlying NUE productivity assumptions were not considered in further statistical analysis. Additional efficiencies associated with recycling of nutrients originating outside the agricultural system are captured by the Nutrient recycling predictor variables (see *Nutrient recycling*).

Given the uncertainty in base year NUE values (*209*), and consistent with our general modelling approach, we use relative change compared to the base year value of each study as the numerical predictor. The following predictor levels were determined for NUE_N / NUE_P based on the reviewed studies:

- Low (0/0%) – NUE_N / NUE_P remains stagnant or oscillates around base year. This setting represents several studies or scenarios that used static N or P footprints (*105, 140*), or assumed current application rates and use intensities (*28, 29, 107*).
- Trend (10/5%) – NUE_N / NUE_P increases at an average historical rate assumed across a range of BAU scenarios in reviewed studies (*86, 93, 180, 210, 213*).
- High (20/10%) – NUE_N / NUE_P increases at twice the BAU rate. This rate of increase corresponds to ambitious scenarios in studies such as (*19, 46, 64, 93*) and is identical for NUE_P but only slightly above the 15% assumed for NUE_N in SSP1 scenarios in (*92*).
- Very high (30/15%) – NUE_N / NUE_P increases substantially. For NUE_N, this level is compatible with the 'Tech+' scenario in (*19, 64, 94*) and Technogarden in (*94*), as well as the combined mitigation scenario in (*42*), but is slightly lower than the sustainable pathway target (38% assuming a baseline NUE_N of 0.46) in (*201*) for NUE_N. Only two studies (*86, 213*) in the database (Data S1) assume considerably higher values but evidence from the field suggests that despite decades of investments in research and development, there are has been limited success in increasing NUE_N (*87, 214*). For NUE_P this corresponds to the most efficient scenarios in (*46, 93*).

Nutrient recycling

The recycling of nitrogen and phosphorus is a highly complementary strategy to boosting nutrient-use efficiency in agriculture, as it has the potential to reduce overall demand and application of chemical N and mined P (*19, 46, 93, 210*). Reducing losses and increasing phosphorus recycling are seen as key to achieving a more closed-loop anthropogenic phosphorus system (*88, 215*). While recycling of N or P within the agricultural system (e.g., from animal manure in grasslands or crop residues) is already incorporated in NUE_N and NUE_P estimates, any recycled P from sources outside this system, such as from imported manure, waste, and human excreta, could also be used to offset requirements for mineral P fertilizer. The recycling of human waste for the purposes of rice cultivation has been practiced for centuries in Asia (*94*). The extent to which this particular P source is likely to have a significant global impact in reducing P fertilizer use and P surplus in agriculture has been debated (*215*). Even though it has been estimated that the complete recycling of all wastes and human excreta would have a relatively limited overall effect (up to ~30% overall reduction) on replacing mineral P fertilizer (*46*), we considered this intervention strategy important enough to warrant the inclusion of dedicated quantitative predictors (one for N and another for P) in our statistical meta-regression models.

The Adapting Mosaic scenario from the Millennium Ecosystem Assessment exemplifies a storyline where this form of nutrient recycling features prominently (*90, 210*). This intervention is also explicitly modelled in (*42, 46, 86, 92, 93, 213*). While some studies and authors explicitly provide the percentages of increased nutrient recycling in their scenarios (*19, 46, 86, 92, 94*), other scenario storylines provide information that allowed an estimation of the percentage recycling of N or P. To consistently control for different levels of implementation of this intervention across studies, we calculated the percentage of nutrient inputs in the agricultural system originating from the recycling of human waste and sewage as a proxy for the overall offset of other forms of nutrients applied to cropland and grassland from within the agricultural system (manure and fertilizer) provided by nutrients recycled from human waste and sewage. A separate metric was calculated for N and P, as follows:

$$N/P_{rec} = \frac{N/P_{human}}{(N/P_{human} + N/P_{manure} + N/P_{fert})} \qquad \text{(Eq. S5)}$$

Where N/P_{rec} is the percentage of recycled N or P contribution to overall N or P in cropland and grassland, N/P_{human} is the amount (in Tg yr^{-1}) of recycled N or P from human waste and sewage used in the agricultural system, and N/P_{manure} and N/P_{fert} are the amounts (in Tg yr^{-1}) of manure and chemical or mined fertilizer applied. While ambitious P recycling scenarios are often (*19*), substantial amounts of N recycling from human waste and sewage only feature in a qualitative storyline in (*46*), with other studies (*42, 86*) finding that the recycling of removed N from wastewater would make a small contribution towards reducing overall fertilizer demand.

Some scenarios also consider efforts to increase manure recycling. Applying manure as an organic fertilizer is a common practice in many parts of the world. In future scenarios, the extent to which this variable can be influential depends on whether there are increased numbers of animals in confined operations (*211*), or whether the storyline dictates that all manure must be recycled (*93, 213*), as in some SSP1 scenarios. We collected data that allowed us to calculated the % of N and P of total available manure N and P recycled on pasture and cropland as a proxy for how much of the total manure gets re-used in the field (both intensive and extensive cropland and grassland systems) minus any losses through volatilization in the case of N, following (*94, 210*). However, this metric could not be adequately harmonized across studies and was therefore not subsequently used as a predictor in the meta-regression models.

In terms of intervention strategies, we focus here on the potential use of recycled P to offset mined P due to its higher recovery potential (*216*) compared to N whose potential to offset chemical N appears more limited (*42*). We established the following percentage levels of recycled P from household waste and sewage in agriculture based on the reviewed literature:

- Low (0%) – This is consistent with most scenarios that assume no additional recycling of household waste and human excreta relative to the current situation and therefore no material contribution of this P source to an extent that offsets mined P (*86*). This setting is also applicable to all studies where nutrient recycling is not explicitly modelled as an intervention (*28, 93, 140, 141, 217*).
- Trend (15%) – This is compatible with increased recycling of household waste and sewage as seen in SSP2 scenarios (*86, 92, 211*).
- High (30%) – This setting is midway between the percentage offset in fertilizer deemed possible in (*46*) and the highly ambitious Tech+ scenario in (*19, 64*) which originates from (*215*).
- Very high (45%) – This percentage is just below the 50% recycling rate assumed in the Tech+ scenario in (*19, 64*).

1.4.3 Other unmodelled interventions in reviewed studies

Organic agriculture

An intervention modelled in some studies is that of conversion from conventional to organic agriculture (*28, 150, 178*). Only 1.4% of current total global farmland is under organic production (*218*). Organic agriculture has the potential to reduce environmental impacts because it avoids the use of off-farm inputs such as synthetic fertilizers and pesticides and promotes locally adapted systems focusing on promoting crop rotations, soil health and biodiversity (*56, 162*). From a planetary boundaries risk perspective, while it does have the potential to significantly reduce fertilizer and pesticide use, organic agriculture tends to require more land than conventional agriculture and there are concerns around reduced productivity (*28, 178*).

Recent studies have modelled scenarios that include different contributions from organic agriculture to the overall food production system (*28, 178*). The extent of organic production is typically defined as the percentage of area or food production under organic agriculture (*28*). To control for this intervention we specifically excluded scenarios that featured organic agriculture (*28, 107*) in N/P fertilizer and surplus-meta regression models but statistically controlled for the potential impacts of organic agriculture by using the percentage of cropland under organic production in the N_2O in order to boost the sample size (Table S19). All other non-organic scenarios were assigned a 0% value under the assumption that they do not include a significant contribution from organic agriculture given no mention of this aspect in their storylines and the very low overall contribution from organic agriculture in study base years.

Trade openness

Global food trade is considered a lever for efficient redistribution of commodities, with many studies considering how boosting production in locations where agriculture is most efficient or where post-harvest losses are lowest could help reduce the overall environmental impacts of the food system (*163, 206*). Scenario storylines with more open trade regimes and economic liberalization are commonly associated with stronger global co-operation on environmental issues and lower overall environmental intensities (*60, 152, 219*). However, this premise is not universally accepted and also depends on the environmental indicator under consideration, with some studies showing potential environmental benefits from more self-sufficient and localized food production systems (*180*). Several studies in our dataset consider alternative trade regimes as deviations from the status quo, either towards more self-sufficiency (i.e., regionalization) or through increased trade (i.e., globalization). While a few studies explicitly specify changes in trade openness as a percentage deviation from the baseline or BAU (*106, 154*), other studies only define the overall trade regime in qualitative terms (e.g., regional or self-sufficient versus more globalized or open). In many cases this is dictated by the underlying SRES, MA, or SSP scenario assumptions (*60, 76, 141, 180*).

Due to the lack of sufficient and consistent information across studies, we did not include a specific predictor for trade in our models. Instead, we controlled for the effects of changing trade regimes and locations of production through the calculation of globally weighted average productivity metrics, namely waste fractions, crop yields, FCR and feed composition, GHG intensities, WUE, and NUE. In the case of (*83*) we also calculated a mean estimate of the dependent variable (cropland) across alternative trade scenarios to derive an average trade scenario.

Disruptive/breakthrough technologies

The overwhelming majority of scenarios in the reviewed studies focused on conventional food production interventions (i.e., currently available technologies and improved management practices) to achieve higher production efficiency through increases in crop yields, livestock feed efficiency, or other efficiency metrics. While significant efficiency gains achieved through these conventional means reflect changes to current practices that are transformational in nature (e.g., new highly productive crop breeds, technological innovation in water resource management), they all fall under the umbrella of *sustainable intensification*

(*220*-*222*) and are readily quantified by assumptions of future changes in the predictor variables described above (especially crop yields, FCR, WUE and NUE).

Examples of food system technologies that are truly *disruptive* or *breakthrough* are those that entail large-scale consumption of so-called 'future foods' such as cellular or cultured meat, mycoprotein, insects, algae, and mussels (*115*); significant global transition to aquaculture-sourced protein (*23*); or alternative animal feed supply routes such as those based on industrial production of microbial proteins (*113*). These foods are characterized as disruptive as they rely on different production systems and supply chains that are less environmentally intensive compared to conventional food production systems (*115*) and because of their potential to become an important element of future sustainable food systems, Only two recent modeling studies have considered truly disruptive or breakthrough technologies. These include artificial meat (*23*) and technologies and feed supplements that can significantly reduce methane emissions in ruminant livestock or capture carbon emissions (*132*). As our chosen predictor variables could not fully capture the advantages or efficiencies of these systems, this variable was not included in any of the models. However, similarly to trade openness, we did not have to exclude the disruptive scenarios (*23*, *132*) from all statistical models as their effect on resource use indicators was partly controlled for by Crop yields, FCRs and feed composition.

1.4.4 Model fitting and selection

LMMs for each planetary boundary indicator

An LMM that follows the standard form of the random intercept model (in matrix notation, as proposed in *223*) was fitted for each indicator (see Table S2), as follows:

$$y_{j,s} = X_{j,s}\beta_j + Z_{j,s}b_{j,s} + \varepsilon_{j,s} \quad \text{(Eq. S6)}$$

where the response variable $y_{j,s}$ is an $n_{j,s}$-length vector of log response estimates for indicator j (e.g., log (future prediction/base year prediction)) where $n_{j,s}$ is the number of scenario projections for indicator j in each study s. $X_{j,s}\beta_j$ is the fixed term where $X_{j,s}$ is an $n_{j,s} \times p_j$ design matrix of the values of the p_j predictor variables for indicator j all $n_{j,s}$ scenarios in each study s, and β_j is a p_j-length vector of the fixed-effects regression coefficients for each predictor variable. The number of predictor variables p_j differs for each indicator as each LMM includes only the relevant predictors. $Z_{j,s}b_{j,s}$ is the random term where $Z_{j,s}$ is the $n_{j,s} \times q$ random effects design matrix containing values for q random effects for all $n_{j,s}$ scenarios in each study s. $b_{j,s}$ is a q-length vector of the random effects. Here, q = 1 since model ID is the only random effect in our 10 LMMs. $\varepsilon_{j,s}$ is the error term represented by a $n_{j,s}$-length vector of the residuals. The model assumes that the random effects $b_{j,s}$ and the errors $\varepsilon_{j,s}$ are normally distributed (*224*). All response variables are continuous with Gaussian distributions, resulting in LMMs with LnR as the response variables to achieve normality and homogeneity of variance. This is similar to the approach recently followed by (*21*) who used percentage change relative to the base year as the response variable. All LMMs were fitted using the R package *lme4* (*225*).

We used a random intercept as opposed to the more flexible random slope model design, as some studies contribute many scenarios whereas others only a few, resulting in unequal and sometimes small lower-level sample sizes (*126*, *226*, *227*). We made an exception in the case of the water and N_2O model where we also allowed a random slope for the yield fixed effects to control for significant differences in the dynamics of models with some explicitly controlling for, while others disregarded, the impact of closing yields gaps on blue water consumption and N_2O emissions respectively. Likelihood ratio tests performed using the *anova* function in base R were used to confirm the suitability of including both random slopes and intercepts in the random effect model structure for these indicators. Following the example of (*228*), we used model ID (as opposed to the more conventional study ID used in meta-analysis) as a random intercept to control for non-independence of scenarios across studies that report runs from a given model type or setup (e.g., GLOBIOM, IMAGE, MAgPIE) characterized by unique modeling assumptions and processes/feedbacks included. This approach also allowed predictions for the mean intercept (model) using the global mean value of the distribution of random effects (*229*). For example, where studies used the same model but report results for different scenarios (*19, 64*), they were assigned the same group model ID. Where models have undergone considerable change through time, we consulted lead authors and modelers about whether a new group model ID was required, e.g. in the case of several studies using different versions of the IMAGE or MAgPIE models.

During data collection we ensured that there were always five or more levels of the random grouping variable, considered as the minimum for achieving robust estimates of variance (*230*). While a more maximal random effect structure (*231*) with two random intercepts, one at the study and another at the model level, was used in a recent study (*21*), this reduced model fits while in our case, while resulting in over-parameterized models and loss of power given available sample sizes, as argued in (*232*). While some inevitable bias and instability may still be present in the LMMs due to the highly variable number of scenarios (some of which had timeseries while others only had 2050 projections) within each study, our chosen model design causes individual study estimates to drift towards the overall mean through shrinkage (an inherent property of mixed-effects models), a phenomenon that is strongest for studies with fewer scenarios (*126, 230*).

Model selection, cross-validation and prediction

While our goal when specifying models was to capture as much relevant information as possible, we chose only pertinent predictors and also carried out necessary aggregation (to derive process-based model variants – see Section 2.3.1) in order to avoid over-parameterization. We selected between alternative fixed effect predictor structures on the basis of model prediction performance. The predictors and their respective levels, detailed above, were selected following discussions with study authors to understand the role of different scenario drivers and their anticipated influence on different indicators. We ensured that all variables for which adequate quantitative data was available either directly from the study, supplied by the authors on request, or calculated as continuous predictors in order to avoid information loss and ensure parsimony (*233, 234*). We fitted the global models using the following procedure:

a. Visual inspection of the distributions of response variables was performed on the basis of Cullen and Frey graphs and quantile-quantile plots using the R packages *fitdistrplus* (*235*) and *car* (*236*). We also compared Akaike Information Criterion (AIC) values of fitted normal, lognormal, and gamma distributions. In all cases, normal distributions had the lowest AIC. We therefore assumed Gaussian distributions and fitted all models as linear mixed models (LMMs), with lnR as the response variables to improve normality and homogeneity of variance. The only exception was the Pasture model where, following (*21*), we used percentage change as the response variable as this produced a more normal distribution. All continuous predictor variables were standardized to improve model stability and the accuracy of parameter estimates given large differences in scale between variables (e.g., between diet-related and productivity predictors) (*237*).

b. We considered alternative fixed and random (in the case of blue water and N_2O) effect structures ranging from the least parsimonious (all variables used as independent predictors), hybrid (selected aggregation of predictors e.g., per capita caloric demand estimates multiplied by population), and most parsimonious (process-based aggregates of independent predictors e.g., total feed demand by livestock type), and evaluated these options through cross-validation, following best practice for predictive models (*128*). This included the testing the addition of an initial condition delta relative to 2010 base year values (see Table S25) following (*101*), The initial condition delta improved the fit for the cropland, blue water, methane, nitrous oxide, and N_{fert} models and was therefore kept as a fixed effect predictor in the selected models for these indicators. We used *repeated cross-validation*, repeating the cross-validation 5 times with alternative fold numbers (over the range 3:*k*, where *k* was the number of random factors minus 1), implemented in the R package *cvms* (*238*) which explicitly controls for the random effect structure in LMMs. We finally selected the model with the best prediction skill (based on RMSE) for each environmental indicator to carry forward to the next stages of model selection and refinements described below.

c. We screened predictors for collinearity based on variance inflation factors (VIFs) adjusted according to degrees of freedom (*239*). Predictors with a VIF > 5 were considered as potentially problematic (*126*). In cases where one or more predictors had a VIF approaching 5 we tested alternative models, where each time one of the predictors were omitted and the resultant models compared based on the AIC criterion using a likelihood-ratio test (Satterthwaite's method) with the *drop1* function in the R package *stats* (*240*). We then selected the predictor combination with the lowest AIC and recalculated the VIFs. If the selected model violated our VIF criterion this step was repeated until an appropriate model with the lowest possible AIC but with all VIFs below 5 was identified.

d. The specified global model was fitted as a LMM with restricted maximum likelihood estimation using the R package *lme4* (*225*). To test for homogeneity of residual variance, we examined normalized residuals versus fitted values for the entire model, for each study, and for selected explanatory variables (*126, 224*). To test for normality of the residuals, we used QQ plots and plots of Pearson residuals. Where the fitted model did not fully meet the assumption of normalized residuals, we also used Cook's distance metrics (using the *car* package) to establish the observations most responsible for introducing error to the model. For models that slightly violated such assumptions but were established to have the highest predictive accuracy through repeat cross-validation, a robust version of the LMM was fitted to confirm that the model coefficients were not being biased by residuals or heteroscedasticity using the *robustlmm* package (*241*), following the example of (*242*). Recent work highlights that LMMs are often robust to such violations (*243*).

e. To further improve the fit and to achieve a more normal distribution of residuals, we compared the fitted model coefficients in the LMM with those in the robust version and then excluded outliers with a standardized residual greater than 2.5 or 3.0 standard deviations using the *romr.fnc* function in the R package *LMERConvenienceFunctions* (*244*) to better match coefficients in the LMM to those in the robust version, as per (*245*). This ensured that the largest possible number of data points was maintained while improving model fit to ensure that underlying model assumptions we not violated. Decisions made during this stage were also guided by marginal (i.e., variance explained by fixed effects) and conditional (i.e., variance explained by fixed and random effects) R^2 estimates based on the method of (*246*) and calculated using the R package *MuMIn* (*247*). Model performance metrics of the final selected models are presented in Table S13. Full global model summaries, produced using the R package *sjPlot* (*248*), are presented in Section 2.3.3.

f. We finally parameterized all relevant interventions spanning all levels of ambition (Section 1.4.2) according to the fixed effects structure of each selected indicator model. We then generated 2050 projections and associated prediction intervals using the ‘predictInterval’ function in the R package *merTools* (*130*) that draws a sampling distribution for random and fixed effects and then estimates the fitted value across that distribution, providing an efficient approximation to a parametric bootstrap. We used 2000 samples to calculate the 95% prediction interval around the mean, incorporating uncertainty of random and fixed effects, as well as residual variance from the model. We finally averaged the prediction intervals to derive normal distributions and standard deviations for each prediction.

Table S13. Model performance metrics following repeat cross-validation with for selected meta-regression models implemented in the R package *cvms* (*238*). [RMSE = root mean square error, AIC = Akaike Information Criterion, AICc = Akaike Information Criterion corrected for small sample sizes, R^2m = marginal R-squared value, i.e., the percentage of variance explained by fixed effects, R^2c = conditional R-squared value variance, i.e., the percentage of variance explained by fixed and random effects].

Indicator	Model type	RMSE	AIC	AICc	R^2m	R^2c	Effect size metric
Cropland	Process-based	0.13	-2699.28	-2699.12	0.68	0.88	LnR
Pasture	Process-based	0.19	-291.407	-291.247	0.78	0.85	% change
CH_4	Process-based	0.11	-1338.89	-1338.38	0.80	0.96	LnR
N_2O	Process-based	0.19	-768.263	-767.359	0.61	0.92	LnR
CO_2 LUC	Process-based	1655	69841	69841	0.62	0.80	Mt CO_2e yr^{-1}
Blue water	Process-based	0.15	-1619.3	-1618.87	0.79	0.94	LnR
N_{fert}	Process-based	0.15	-1116.21	-1115.72	0.80	0.88	LnR
$N_{surplus}$	Process-based	0.16	-1091.57	-1090.97	0.80	0.92	LnR
P_{fert}	Process-based	0.22	-1150.45	-1149.84	0.82	0.96	LnR
$P_{surplus}/P_{instream}$	Process-based	0.21	-162.131	-158.336	0.84	0.95	LnR

1.4.5 Calculating exceedance risk for modelled projections

To derive exceedance risk estimates for each model prediction in a way that encompassed both uncertainty in environmental limits (Section 1.2) and the uncertainty in the statistical model predictions given by the prediction intervals, we used a simulation-based approach. We calculated the risk of exceeding ($ER_{j,l}$) each indicator *j* for all combinations of predictor variable levels *l* (see Table 2 in main manuscript) as:

$$ER_{j,l} = P(Y_{j,l} > X_j) \quad \text{(Eq. S7)}$$

where $Y_{j,l}$ is a random draw from the normal distribution of the LMM estimate (mean = prediction estimate and SD = standard deviation of prediction estimates (see step f. in Section 1.4.4). X_j is a random draw from the probability density function representing the uncertainty in environmental limits for each planetary boundary (Table S2). Both $Y_{j,l}$ and X_j are expressed in native units. We approximated both distributions by taking 10,000 random draws using the R packages *stats* (*240*) and *extraDistr* (*249*). Fig. S2 illustrates the *ER* calculation for the land-system change planetary boundary in the case where all interventions are set to their Trend level (see Table S25 for all Trend level projections).

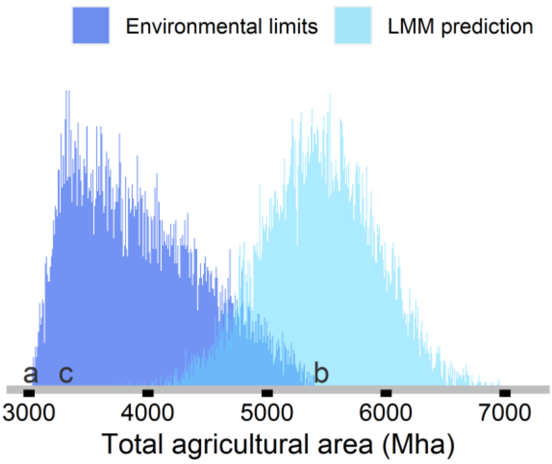


Fig. S2. Illustrative example of the *ER* calculation method to account for uncertainty in LMM predictions and environmental limits. ER for land-system change is calculated as the probability of a random value from the normal distribution of prediction estimates (Mean = 5441 Mha, SD = 487 Mha) exceeding a random value from the triangular distribution of land-system change environmental limits (a = 3019 Mha, b = 3309 Mha, c = 5460 Mha), based on 10,000 random draws from each respective distribution. *ER* = 0.98 in this case.

1.4.6 Establishing risk-compliant combinations

To enable the final mapping of the performance of all intervention combinations against their risk mitigation and ambition level we merged all risk results for each planetary boundary into one integrated dataset based on matching intervention levels across all the common interventions (available across all indicator statistical models): population, diet change (animal and plant calories), waste reduction, crop yields, feed efficiency (FCR), and feed composition. The resulting dataset spanned 2,097,152 plausible intervention level combinations across all boundaries (Table S14).

Table S14. Modelled interventions and total intervention-level combinations for each planetary boundary and combined for all planetary boundaries.

Planetary boundary	Interventions included	Total combinations	Common interventions (+additions)
Land-system change	7	$4^7 = 16,384$	Animal kcal, Plant kcal, Waste, Crop yields, FCR, FCF.
Climate change	8	$4^8 = 65,536$	+ Climate action
Freshwater use	8	$4^8 = 65,536$	+ WUE
Biogeochemical flows	8	$4^8*2 = 131,072$	+ NUE/PUE. Both were allowed to vary independently of each other to create two pooled risk datasets for N & P respectively.

Planetary boundary	Interventions included	Total combinations	Common interventions (+additions)
Integrated dataset	11	2,097,152	The four individual planetary boundary indicator results were merged on the basis of common interventions starting from land-system change. This resulted in a total of 16,384*4*4*4*2 combinations.

Using the integrated dataset with all intervention-level combinations across all boundaries, we then filtered the scenarios that met two critical IPCC-calibrated uncertainty risk thresholds (*250*) across all boundaries: < 0.50 risk (exceedance *about as unlikely as not*) and < 0.33 risk (exceedance *unlikely*) and categorized them in terms of the type and level of each intervention required to achieve each threshold. The selected scenarios can be presented in Pareto plots in Fig. S6 that illustrate the trade-off between intervention level (calculated as the average ambition level across all relevant interventions) and exceedance risk (calculated as per Fig. S2). carried out additional analysis to calculate.

2 Supplementary Text

2.1 Additional calculations and data harmonization

Our priority when extracting and compiling the data was to maximize sample sizes across all indicators while ensuring the highest quality datasets with the most complete set of input variables. A primary means for achieving this was to maximize the number of studies and scenarios included in our final dataset (Data S1). Many published articles or reports did not report all relevant parameters (see Table S5) for each scenario. This required significant additional efforts to source and harmonize data to ensure compatibility between studies.

Several additional calculations and unit conversions based on established conversion factors, were necessary to ensure a harmonized dataset compatible with planetary boundary indicators (see notes in T1 Data S1). All data containing original values supplied by the study authors along with any additional R scripts containing additional calculations carried out during the compilation of the input database (Data S1) are available on request.

2.1.1 Global weighted averages

A disaggregated regional analysis was not possible due to the heterogeneous definitions of regions used between studies. For this reason, where input parameters (see Table S5) were reported or directly supplied by study authors as regional per capita averages (Data S1), we calculated the population- or production- weighted global averages. The equation below presents an example for calories, as follows:

$$x_{WORLD2050} = \sum_{i=1}^{n} \left(x_{i2050} * \frac{Pop_{i2050}}{Pop_{WORLD2050}} \right) \qquad \text{(Eq. S8)}$$

where $x_{WORLD2050}$ is the weighted global average caloric intake for 2050, *n* is the number of regions used in the study (*n* varies depending on the study as studies tend to use different regional classification), and Pop_{i2050} and $Pop_{WORLD2050}$ are the regional and global populations, respectively.

In studies that provided food consumption excluding waste (*19*, *23*, *64*, *76*), an additional regional weighting factor was added to convert food consumption to food supply as per the FAOSTAT Food Balance Sheet definition, using cumulative waste estimates encompassing all stages of production and final consumption (*155*). In cases where food demand was expressed in mass units, we used mass-to-calorie conversion factors calculated from (*142*) to ensure all food supply data was expressed in comparable caloric terms. These converted food supply estimates were shared with the respective study authors who approved their use. This procedure ensured compatibility across all studies inclusive of waste.

Where only regional or country-level data were provided, we calculated production-weighted global averages for all efficiency metrics such as crop yields, FCR and feed composition, GHG intensities, WUE, and NUE, in order to control for spatial reallocation in production as well as to control for other unmodelled parameters such as trade (see Section 1.4.2).

2.1.2 Handling of scenarios with changes in biofuel and other non-food demand

Given our focus on food and feed demand, our study scope and search strategy excluded studies with a focus on changes in future demand for biofuels and other crops (i.e., fibre and industrial crops) not used for food or feed (see Fig. S1 and Section 1.1.4). However, several studies (or selected scenarios within studies) included storyline elements that involved future demand changes with significant implications that needed to be controlled for in the analysis. In accordance with our priority to maximize study sample sizes and scenario numbers, we followed a workflow (Fig. S3) to control for any additional crop demand associated with biofuels and non-food crops on a study-by-study basis.

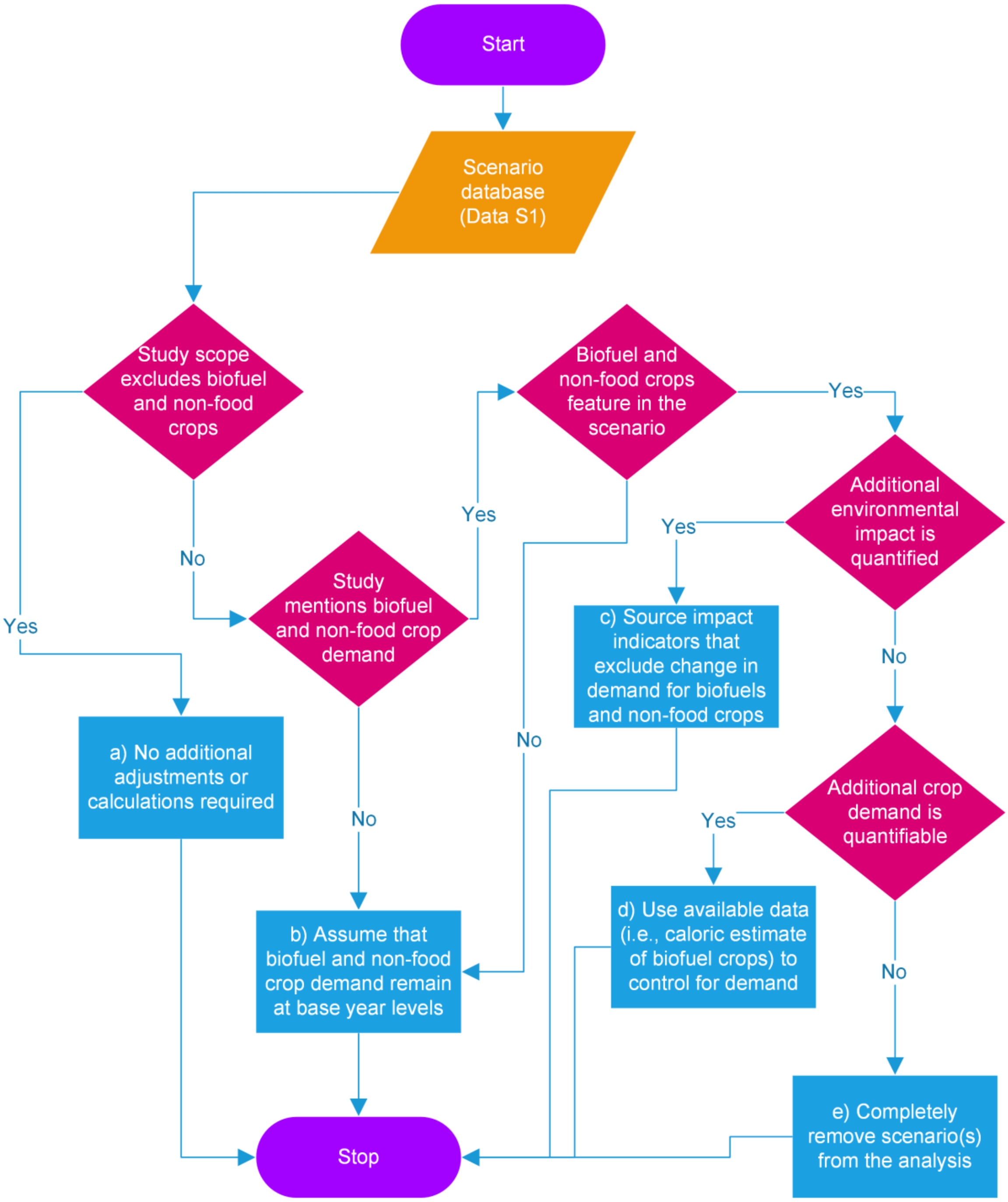


Fig. S3. Workflow diagram illustrating the steps followed to control for biofuel and non-food crop demand in relevant scenarios across all selected studies.

Following Fig. S3, the 35 studies that contained the full suite of necessary input and output data (see Data S1) and were therefore eligible for training the meta-regression models (see Table S4 & Table S5) were classified as follows:

a) Eight (8) studies (*19*, *23*, *40*, *64*, *83*, *141*, *150*, *217*) employed food systems models or approaches that completely excluded biofuel and non-food crops from their base year or future scenarios. In this case we made no adjustments to any of the output (indicator) or input variables.
b) Fourteen (14) studies (*28, 31, 42, 46, 76, 86, 94, 105, 132, 135, 140, 153, 164, 165*) considered base year impacts (e.g., cropland area used for biofuel and non-food crops) but held demand and associated impacts from biofuel and non-food crops constant into the future, reflecting their absence from any of the scenario storylines. Some studies note that for base years at or before 2010 the amount of global cropland area used by biofuel and non-food crops was very low compared to food and feed crops (*109, 164*).
c) Eight (8) studies (*75, 92, 93, 107, 152, 193, 194, 213*) included scenario storylines (e.g., SSPs) that assumed changes in future biofuel demand that make a material contribution to differences in environmental impact but also provided disaggregated results. In these cases, we used future environmental impact estimates that only accounted for the additional demand in food crops along with compatible food-specific input variables (e.g. caloric totals). Studies also assume that demand for non-food competing second-generation biofuels (cellulosic ethanol feedstocks and wasted vegetable oils and fats) is likely to grow further, whereas biomass feedstock for first-generation biofuels is expected to decline (*75, 152, 194*).
d) Three (3) studies (*60, 61, 154*) also assumed changes in future biofuel and non-food crop demand with important implications on aggregate environmental impact but did not provide disaggregated results of these additional impacts. However, production totals of the crops used exclusively for non-food uses were available through supplementary data that allowed estimates of caloric demand using crop-specific mass-to-calorie conversion factors calculated from (*142*). We note that in (*61*) there may have been some unaccounted-for demand for non-food crops due to inherent limitations in the version of GCAM used in that study that did not allow a complete partitioning of crop demand according to its use.
e) Two (2) studies (*149, 210*) had scenarios with strong biofuel assumptions but we were unable to disaggregate any input or output data to allow us to control for this additional demand as per the studies in c) or d) above. We therefore eliminated these scenarios from the analysis. Specifically, in the case of (*210*) we eliminated the Technogarden 2050 projection as this entailed >500Mha of cropland used for energy crops but we did not have estimates of the amount of N and P associated with these crops. In (*149*) we did not consider the scenario variant that entailed a major expansion of first-generation biofuels. These scenario eliminations had minimal impact on sample sizes as, in both cases, we included all other scenarios that assumed zero or negligible non-food demand changes.

2.2 Greenhouse gas emissions

2.2.1 Non-CO_2 GHG emission categories

The following direct emission categories were included in the analysis (see Data S1 for full GHG emissions breakdown) consistent with IPCC Agriculture in AR6 (*35, 73*) and with FAOSTAT 'within the farm gate' emission categories (*251, 252*):

- CH_4 from enteric fermentation.
- CH_4 from rice cultivation.
- CH_4 from manure management
- N_2O from manure management
- N_2O associated with agricultural soils including synthetic fertilizers, biological fixation, manure left on pasture, manure applied to crops, crop residues and cultivated organic soils. Many studies only included a single aggregated category while others included slightly more detailed classifications distinguishing between manure and fertilizer categories.

All estimates were sourced in their respective native units (see Data S1) and were fully harmonized using the revised AR6 global warming potential (GWP-100) factors of 27.2 for biogenic CH_4 and 273 for N_2O (*253*). CH_4 and N_2O associated with crop residue and savannah burning and indirect N_2O emissions from aquatic ecosystems were not included in the analysis as these emission categories were not provided in most papers and only account for a <10% of total agriculture emissions (*251*).

2.2.2 Modelling CO_2 associated with land-use change

Agriculture emissions from land use and land-use change activities are highly uncertain (*78, 254*), with studies often adopting different assumptions with respect to the biophysical processes and emission sources included (*54, 255*). This is also the case for the studies in our database as determined following an audit of all 11 studies that included CO_2 LUC estimates (Data S1). We also ascertained that training a statistical model based on the LUC estimates from published studies would produce estimates that would not be compatible with our climate change planetary boundary (Table S2) or our cropland and pasture storylines and predictions. For this reason, we did not fit a model using the LUC data presented in our database, which have nevertheless been compiled for completeness, with notes indicating the processes included or excluded (see T4, Data S1).

Similarly to (*40*), our agricultural land use estimates (cropland and pasture in our case) are global totals which creates a challenge in estimating land use change emissions because agricultural land expansion and abandonment occurs at national and subnational scales, with spatial patterns of land use change the key determinant of the ecosystems and respective carbon stores being impacted (*76, 109*). Using our estimates of cropland and pasture, we calculated annual change (ha yr^{-1}) for the period 2010-2050 by subtracting the base year estimates from the 2050 projection estimates. We assumed a constant clearing rate during this period, as per (*109*).

We then explored two alternative approaches. The first was based on average figures of emissions and sequestration per hectare associated with cropland expansion (+333 tonnes CO_2) and abandonment (-211 tonnes CO_2) from the period 2006 to 2010 using spatial estimates of carbon stores in living biomass and soil coupled with patterns of land clearing over the previous decade (*40*). While this approach produced figures of annual CO_2 LUC emissions comparable to the literature (*40*) when coupled with our cropland predictions, it did not account for emissions associated with pasture expansion (*76*) and could also not be integrated with other intervention settings such as carbon price to ensure storyline compatibility with assumptions round non-CO_2 GHG intensity. We therefore adopted an alternative approach.

Using a large sample of 4,835 CO_2 LUC estimates spanning the period 2010-2050 representing all land use models runs used in IPCC AR6 (*73, 255*) available in the Integrated Assessment Modeling Consortium (IAMC) AR6 Scenario Database (*35*) for models already represented in our database, we fitted an additional LMM with annual change in CO_2 LUC emissions (*delta LUC emissions*, or 'Emissions|CO2|AFOLU' as per the AR6 nomenclature) as the dependent variable, and annual change in cropland (*delta cropland*), pasture (*delta pasture*), carbon price, afforestation beyond regrowth associated with agricultural abandonment/expansion (*delta afforestation*), and year as fixed effect predictors. Following the example of (*228*), we assigned Model ID as the random factor to account for the association of data associated with each model, thus controlling for the variation between models. We followed the same sequence of steps for model selection, and tests for collinearity and outliers as previously described in Section 1.4.4 (see also Table S13 for cross-validation statistics and Table S20 for final model summary). To generate predictions, we used our annualized estimates for cropland and pasture expansion/abandonment along with the four carbon price settings (0-\$200 t CO_2^{-1}). In our predictions we also set *delta afforestation* equal to zero as we do not consider CO_2 sequestration associated with afforestation efforts beyond regrowth in abandoned areas, and the year to 2030 to reflect the possible locations of land-use change occurring during the mid-point of the 2010-2050 period. Our 2050 BAU mean projection of 3.52 (SD = 1.16) Gt CO_2e associated with 2029 (SD = 156) Mha of cropland and 3412 (SD = 462) Mha of pasture area is comparable to the MAgPIE BAU projection of ~3.75 Gt CO_2e (*108, 256*) while the upper estimate (mean + 2*SD) is comparable to the IMAGE estimate of ~6 Gt CO_2e (*256*).

A number of important assumptions and caveats need to be acknowledged. As per (*40*), we only considered CO_2 GHG emissions associated with land use change and we allocate all emissions to the year of agricultural expansion/abandonment. We assumed independence and no collinearity between fixed effects terms, as confirmed by VIFs <3. Our statistical approach also assumes that, on average, the emissions and sequestration associated with each hectare of cropland/pasture expansion and abandonment are the same despite known differences between deforestation and reforestation carbon exchange parameters (*76, 109*). Carbon sequestration associated with biomass supplied for bioenergy coupled with carbon sequestration (BECCs) is outside the scope of the analysis as this is attributed to the energy sector as opposed to the agriculture sector in IPCC AR6 land use models (*255*).

2.3 Model variables and summaries

2.3.1 Model parameterization and variable selection

As previously described (Section 1.4.4), for each indicator we tested alternative fixed effects structures ranging from the least parsimonious (all relevant variables used as independent predictors) to more parsimonious (process-based aggregates of variables used as independent predictors). As per Table S13, the selected models were those that used process-based composite variables as predictors due to both due to their superior inference and improved prediction skill. The following sub-sections summarize the parameterization logic behind the choice of composite variables (see Section 2.3.2) used in each statistical model (see Section 0).

Land-system change

We assumed that cropland extent is determined by the total demand (consumption + waste) for food crops (see Eq. S9) in addition to feed requirements for monogastric and ruminant livestock products (*109*). Crop yield increases can reduce overall cropland demand whereas higher feed efficiencies or changes in feed composition (i.e., reductions in the food-competing feed fraction) across each livestock type can offset their respective demands for feed. We excluded studies where cropland was not an explicit output of the modelling (*86*, *164*, *205*), studies that had very limited crop coverage (*141*, *165*), and also scenarios in (*23*) that assumed no feed from pasture.

We assumed that pasture extent is determined by the total demand (consumption + waste) for grazing animals, namely ruminant meat (beef cattle, sheep and goats) and dairy cattle (see Eq. S20). Higher feed efficiencies or changes in feed composition (i.e., increases in the food-competing feed fraction) across each livestock type can then offset demand for pasture-derived feed. Similarly to cropland, we excluded studies where pasture was not an explicit output of the modelling (*164*), as well as studies (*28*) and scenarios (*23*) that kept pasture area constant.

Freshwater use

We assumed that blue water consumption is primarily driven by irrigation requirements for growing food (Eq. S9) and feed crops (Eq. S17), the latter of which is a product of the amount and type of animal products consumed along with their respective feed efficiency and feed composition (*257*). We allowed a random slope for the yield fixed effects to control for the heterogeneity that exists between the underlying models in terms of the relationship between crop yields and water (see Section 1.4.4). Higher feed efficiencies and changes in feed composition (i.e., reductions in the food-competing feed fraction) across each livestock type were assumed to reduce demand for crop feed and associated irrigation requirements (*135*). Total plant calories (Eq. S9) and water-use efficiency (defined as the ratio of crop yield to the volume of water consumed, see Section 1.4.2) were also added as fixed effects predictors. We excluded studies that had limited crop coverage (*205*) or did not model the relationship between crop yields and water demand (*105*).

Climate change

To model CH_4, we defined composite predictors to cover the three key sources: enteric fermentation, manure management, and rice cultivation (see Section 2.2.1). We assumed that ruminant meat and dairy supply acts as the key determinant of enteric fermentation, with enteric fermentation from non-ruminant animals known to be very modest in comparison (*258*). To capture CH_4 associated with manure management we specified composite predictors that also account for the total amount of feed in both ruminant (Eq. S21) and non-ruminant animals (Eq. S23) as a determinant of total manure production, controlling also for livestock productivity, which in turn determines livestock numbers and feed demand (*174*). Total plant calories (Eq. S9) were used as a proxy for rice demand and we also fitted a cereal crop yield variable as a unique fixed effect predictor. Higher yields in rice paddies have been shown to reduce methane emissions since methane emissions are correlated to paddy area rather than the quantity of production (*132*). A CH_4 intensity predictor (calculated as a weighted average across all CH_4 emission components, as detailed in Section 1.4.2) was also added as a fixed effects predictor. While our selected predictors incorporate the positive impact of lower FCRs on CH_4 from enteric fermentation and manure, our statistical models and the granularity of our feed data did not allow us to model the impact of feed composition (*174*). We excluded studies that did not provide a breakdown of non-CO_2 emissions (*19, 64*).

To model N_2O, we defined composite predictors to cover all key sources: agricultural soils (synthetic fertilizer and manure left on pasture are by far the most dominant sources) and manure management from confined animal operations (see Section 2.2.1). We assumed that both crop (Eq. S17) and grass feed (Eq. S20) require nutrient fertilization and assigned separate predictors in each case to account for the differences in N_2O emission processes associated with cropland and pasture (*259*). This was also intended to capture potential trade-offs, as in the case where reduced N_2O emissions from fertilizer application due to a shift in feed composition away from crop feed towards grass feed (i.e., reductions in FCF) could be outweighed by nitrogen oxidation from manure and leguminous forage (*260*). We also assumed that manure production is proportional to total feed intake (*258*). As in the case of blue water consumption, we allowed a random slope for the yield fixed effects to control for the heterogeneity that exists between the underlying models in terms of the relationship between crop yields and N_2O (see Section 1.4.4). Total plant calories (Eq. S9) and a N_2O intensity predictor (calculated as a weighted average across all CH_4 emission components, as detailed in Section 1.4.2) in addition to a predictor controlling for the percentage of land under organic production (see Section 1.4.3) were also added as fixed effects predictors. We excluded studies for which the upstream CO_2 emissions associated with fertilizer production could not be separated (*40*), and studies with unresolved issues around the breakdown of N_2O emissions into different sources (*23, 107*).

For parameterization of the CO_2 LUC model please see Section 2.2.2.

Biogeochemical flows

For the N_{fert} and P_{fert} models we assumed that fertilizer application is driven primarily by food and feed crops, the latter of which is a product of the amount and type of animal products consumed along with their respective feed efficiency and feed composition. This is consistent with (*209*) who reported that <5% of fertilizer nitrogen is applied to grassland. While in the N_{fert} model we distinguished between ruminant and non-ruminant crop feed (see Eq. S15 and Eq. S16), for P_{fert} we aggregated all crop feed into one single predictor (Eq. S17) to avoid collinearity. Similarly to the other models, we also fitted fixed effects predictors for total plant calories (see Eq. S9) and crop yields. In addition, we fitted two separate fixed effects predictors to control for the level of nutrient-use efficiency (NUE_N / NUE_P) and nutrient recycling (N/P_{rec}) following the approach detailed in Section 1.4.2. Studies with very few numbers of scenarios (*217*), those that lacked consistent NUE and yield metrics (*140, 141*), and scenarios with organic agriculture (*107*) were excluded.

For the $N_{surplus}$ and $P_{surplus}$ models, we also accounted for the significant impact of manure from pasture, which contributes significantly to agricultural N and P surplus (*94*). We did this by assigning separate predictors for monogastric feed (Eq. S15) and ruminant feed (Eq. S20 for $P_{surplus}$ and Eq. S21 for $N_{surplus}$ in order to address collinearity issues). As in the case of the N_{fert} and P_{fert} models, we also fitted fixed effects predictors for total plant calories (see Eq. S9), crop yields, and nutrient-use efficiency (NUE_N / NUE_P). We did not consider nutrient recycling (N/P_{rec}) for surplus indicators as recycling of household waste and/or wastewater has minimal impact on surplus over agricultural land (*42*). We excluded (*28*) from the $N_{surplus}$ model due to radically different base year starting values and all organic scenarios from (*28*) that assumed negative surplus in the $P_{surplus}$ model.

2.3.2 Composite variables used as predictors

The following equations describe the calculation of the composite variables presented in the selected model summaries (Section 0).

$$TotalSupply_p = Population * FoodSupply_p \quad \text{(Eq. S9)}$$

$$TotalSupply_r = Population * FoodSupply_r \quad \text{(Eq. S10)}$$

$$TotalSupply_d = Population * FoodSupply_d \quad \text{(Eq. S11)}$$

$$TotalSupply_m = Population * FoodSupply_m \quad \text{(Eq. S12)}$$

$$CropFeed_r = TotalSupply_r * FCR_r * FCF_r \quad \text{(Eq. S13)}$$

$$CropFeed_d = TotalSupply_d * FCR_d * FCF_d \quad \text{(Eq. S14)}$$

$$CropFeed_m = TotalSupply_m * FCR_m * FCF_m \quad \text{(Eq. S15)}$$

$$CropFeed_{rd} = CropFeed_r + CropFeed_d \quad \text{(Eq. S16)}$$

$$CropFeed_{rdm} = CropFeed_{rd} + CropFeed_m \quad \text{(Eq. S17)}$$

$$GrassFeed_r = TotalSupply_r * FCR_r * (1 - FCF_r) \quad \text{(Eq. S18)}$$

$$GrassFeed_d = TotSupply_d * FCR_d * (1 - FCF_d) \quad \text{(Eq. S19)}$$

$$GrassFeed_{rd} = GrassFeed_r + GrassFeed_d \quad \text{(Eq. S20)}$$

$$AllFeed_{rd} = GrassFeed_{rd} + CropFeed_{rd} \quad \text{(Eq. S21)}$$

$$OtherFeed_m = TotalSupply_m * FCR_m * (1 - FCF_m) \quad \text{(Eq. S22)}$$

$$AllFeed_m = CropFeed_m + OtherFeed_m \quad \text{(Eq. S23)}$$

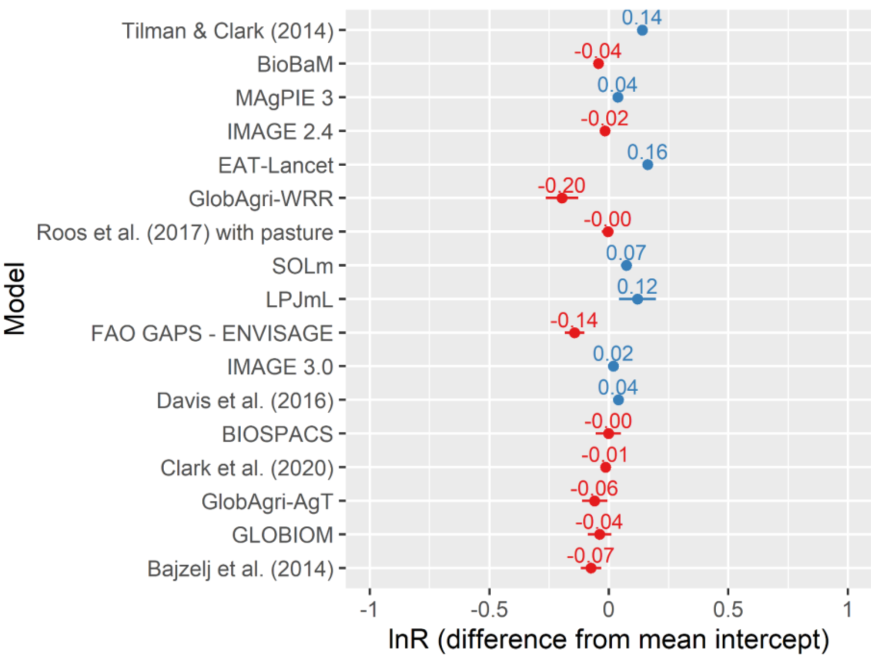
where *r* are ruminant meats (beef, mutton and goat), *d* is dairy (milk excluding butter), *m* are monogastric products (chicken, pork, eggs, and aquaculture), *p* are all crops directly consumed by humans, *FCR* is the feed conversion ratio, and *FCF* is the ratio of feed from crops in direct competition with food. *rd* is used when referring to combined totals for all ruminant animals. All variables are standardised as multipliers relative to their base year value across each study. $TotalSupply$ estimates were converted from kcal to kg based on disaggregated commodity energy to mass conversions in the FAOSTAT 2010 balance sheets (*142*) to ensure compatibility with FCR units. $OtherFeed_m$ refers to non-FCF residues and by-products as per (*28, 29*).

2.3.3 Statistical model summaries

Below we present the model summaries of each of the LMMs fitted using the R package *lme4* (*225*) along with robust LMM versions fitted using the R package *robustlmm* (*241*) for each of the environmental indicators. Each table presents fixed effect coefficients and their confidence intervals, random effect attributes including mean random effect variance (σ^2), random intercept variance ($\tau 00$), intra-class correlation coefficient (ICC, calculated as random intercept variance over total variance) and number of groups (N_{Study}), and overall model goodness-of-fit estimates such as the Akaike information criterion (AIC). For variable definitions see Section 2.3.2). %Δ denotes change relative to the base year value. All tables were produced with the R package *sjPlot* (*261*).

Table S15. Cropland (LnR) model summary.

	Cropland (LMM)			Cropland (robust LMM)		
Predictors	*Estimates*	*CI*	*P*	*Estimates*	*CI*	*p*
(Intercept)	0.02	-0.07 – 0.03	0.354	0.01	-0.07 – 0.03	0.393
CropFeed$_r$ (%Δ)	0.02	0.01 – 0.02	**<0.001**	0.02	0.01 – 0.02	**<0.001**
CropFeed$_d$ (%Δ)	0.04	0.04 – 0.05	**<0.001**	0.05	0.04 – 0.05	**<0.001**
CropFeed$_m$ (%Δ)	0.07	0.06 – 0.07	**<0.001**	0.07	0.06 – 0.07	**<0.001**
TotalSupply$_p$ (%Δ)	0.11	0.10 – 0.11	**<0.001**	0.11	0.10 – 0.11	**<0.001**
Crop yields (%Δ)	-0.15	-0.15 – -0.14	**<0.001**	-0.15	-0.15 – -0.14	**<0.001**
Initial condition delta	0.03	-0.00 – 0.06	0.053	0.04	0.00 – 0.07	**0.037**
Random Effects						
σ^2	0.01			0.01		
τ_{00}	0.01 Model			0.01 Model		
ICC	0.63			0.59		
N	17 Model			17 Model		



	Cropland (LMM)	Cropland (robust LMM)
Observations	1380	1421
Marginal R^2 / Conditional R^2	0.690 / 0.884	0.699 / 0.877
AIC	3106.190	
AICc	-3106.059	

Table S16. Pasture (delta %) model summary.

	Pasture (LMM)			Pasture (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.22	-0.28 – -0.16	**<0.001**	-0.21	-0.28 – -0.14	**<0.001**
GrassFeed_{rd} (%Δ)	0.35	0.34 – 0.37	**<0.001**	0.36	0.35 – 0.38	**<0.001**
Initial condition delta	-0.02	-0.05 – 0.02	0.332	-0.01	-0.05 – 0.02	0.374
Random Effects						
σ^2	0.02			0.02		
τ_{00}	0.01 $_{\text{Model}}$			0.01 $_{\text{Model}}$		
ICC	0.30			0.37		
N	13 $_{\text{Model}}$			13 $_{\text{Model}}$		
Observations	455			470		
Marginal R^2 / Conditional R^2	0.783 / 0.848			0.784 / 0.864		
AIC	-347.108					
AICc	-346.977					

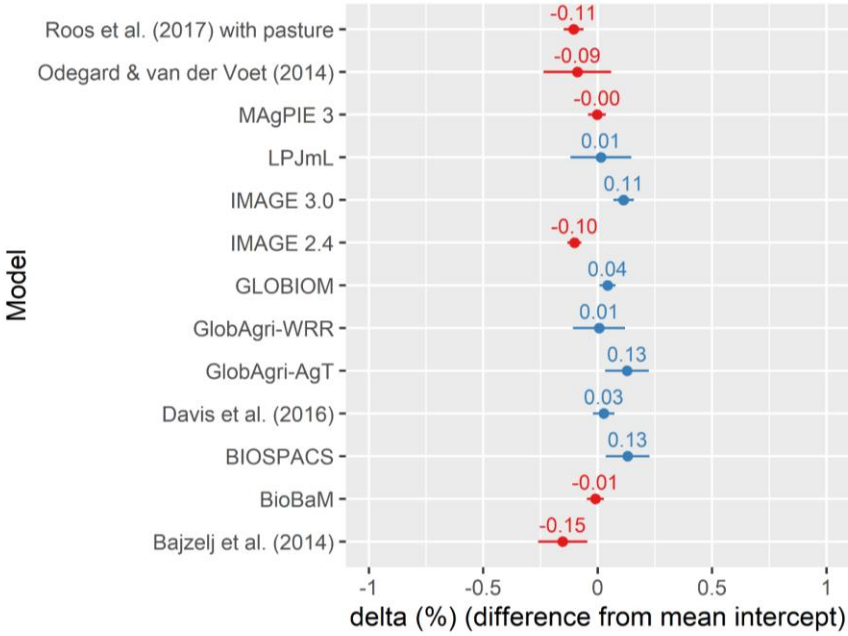
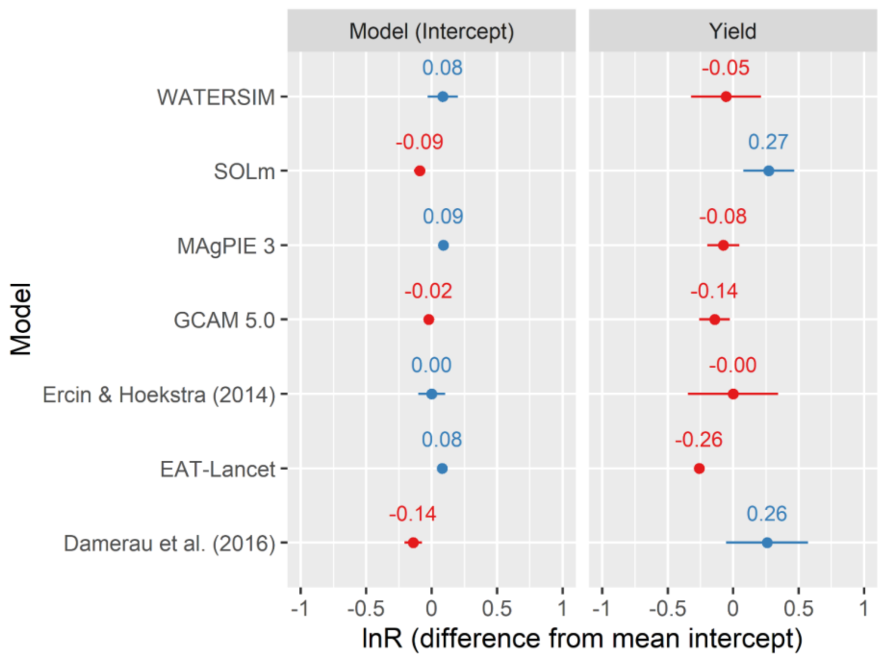


Table S17. Blue water consumption (LnR) model summary.

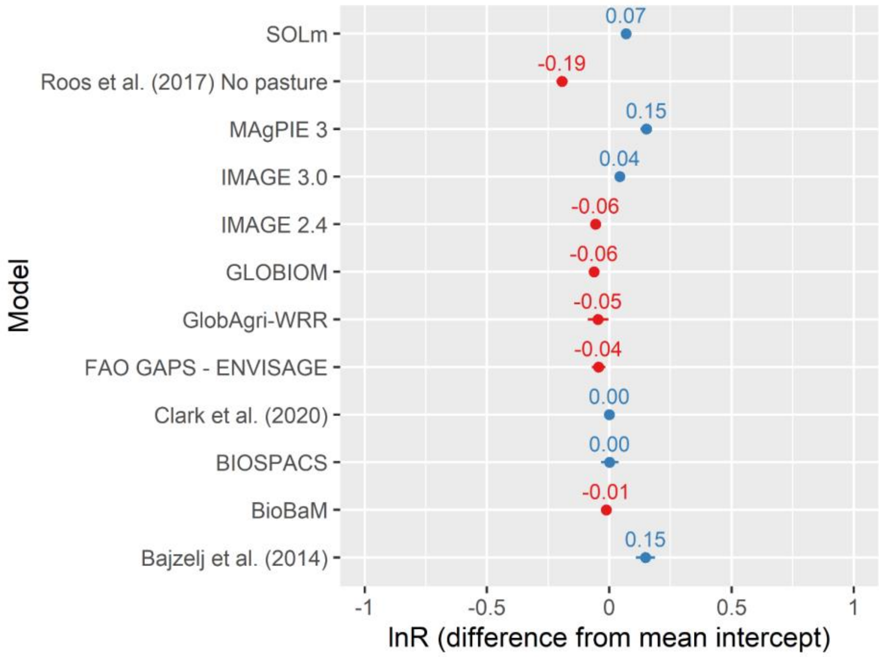
	Blue water (LMM)			Blue water (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.07	-0.12 – -0.01	0.016	-0.06	-0.12 – -0.01	0.030
CropFeed$_{rdm}$ (%Δ)	0.04	0.03 – 0.04	**<0.001**	0.04	0.03 – 0.04	**<0.001**
TotalSupply$_{p}$ (%Δ)	0.14	0.14 – 0.15	**<0.001**	0.14	0.14 – 0.15	**<0.001**
Crop yields (%Δ)	0.04	-0.00 – 0.07	0.051	0.03	-0.01 – 0.08	0.098
WUE (%Δ)	-0.14	-0.15 – -0.13	**<0.001**	-0.14	-0.15 – -0.12	**<0.001**
Initial condition delta	-0.03	-0.05 – -0.02	**<0.001**	-0.03	-0.05 – -0.02	**<0.001**
Random Effects						
σ^2	0.00			0.00		
τ_{00}	0.01 $_{\text{Model}}$			0.01 $_{\text{Model}}$		
τ_{11}	0.05 $_{\text{Model.Yield}}$			0.07 $_{\text{Model.Yield}}$		
ρ_{01}	-0.77 $_{\text{Model}}$			-0.82 $_{\text{Model}}$		
ICC	0.71			0.74		
N	7 $_{\text{Model}}$			7 $_{\text{Model}}$		



Observations	732	735
Marginal R^2 / Conditional R^2	0.798 / 0.942	0.782 / 0.943
AIC	-1886.779	
AICc	-1886.474	

Table S18. Methane (LnR) model summary.

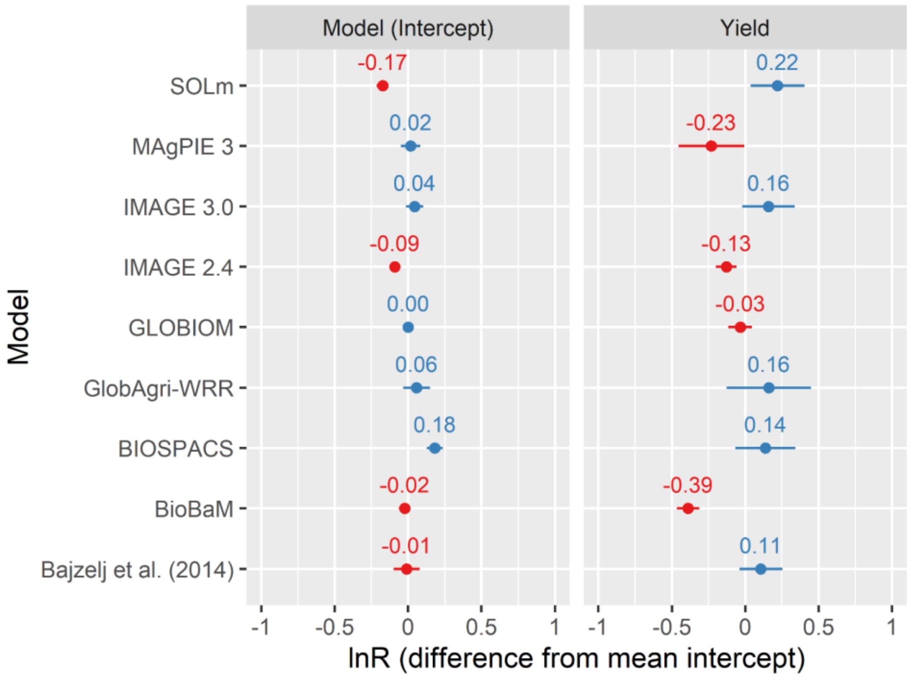
	CH_4 (LMM)			CH_4 (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.08	0.02 – 0.13	0.005	0.08	0.03 – 0.13	**0.001**
$AllFeed_r$ (%∆)	0.17	0.16 – 0.18	**<0.001**	0.18	0.17 – 0.18	**<0.001**
$AllFeed_d$ (%∆)	0.08	0.07 – 0.09	**<0.001**	0.08	0.08 – 0.09	**<0.001**
$AllFeed_m$ (%∆)	0.02	0.02 – 0.03	**<0.001**	0.02	0.01 – 0.02	**<0.001**
$TotalSupply_p$ (%∆)	0.01	0.01 – 0.02	**<0.001**	0.01	0.01 – 0.02	**<0.001**
Crop yields (%∆)	-0.02	-0.02 – -0.01	**<0.001**	-0.02	-0.02 – -0.01	**<0.001**
CH_4-intensity (%∆)	-0.10	-0.10 – -0.09	**<0.001**	-0.10	-0.10 – -0.09	**<0.001**
Initial condition delta	-0.04	-0.06 – -0.02	**<0.001**	-0.03	-0.05 – -0.02	**<0.001**
Random Effects						
σ^2	0.00			0.00		
τ_{00}	0.01 Model			0.01 Model		
ICC	0.79			0.82		
N	12 Model			12 Model		



Observations	548	556
Marginal R2 / Conditional R2	0.805 / 0.960	0.853 / 0.974
AIC	-1601.111	
AICc	-1600.701	

Table S19. Nitrous oxide (LnR) model summary.

	N_2O (LMM)			**N_2O (robust LMM)**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.13	0.05 – 0.22	**0.003**	0.14	0.05 – 0.23	**0.003**
$GrassFeed_{rd}$ (%Δ)	0.10	0.09 – 0.10	**<0.001**	0.10	0.09 – 0.10	**<0.001**
$CropFeed_{rdm}$ (%Δ)	0.12	0.11 – 0.13	**<0.001**	0.12	0.12 – 0.13	**<0.001**
$TotalSupply_{p}$ (%Δ)	0.05	0.03 – 0.06	**<0.001**	0.04	0.03 – 0.06	**<0.001**
Crop yields (%Δ)	0.01	-0.02 – 0.04	0.560	0.01	-0.03 – 0.05	0.562
N_2O-intensity (%Δ)	-0.08	-0.09 – -0.07	**<0.001**	-0.08	-0.09 – -0.07	**<0.001**
Organic area (%)	-0.06	-0.07 – -0.05	**<0.001**	-0.06	-0.07 – -0.05	**<0.001**
Delta initial	-0.04	-0.05 – -0.02	**<0.001**	-0.04	-0.05 – -0.03	**<0.001**
Random Effects						
σ^2	0.01			0.00		
τ_{00}	0.01 $_{Model}$			0.01 $_{Model}$		
τ_{11}	0.05 $_{Model.Yield}$			0.06 $_{Model.Yield}$		
ρ_{01}	0.00 $_{Model}$			-0.03 $_{Model}$		
ICC	0.67			0.72		
N	9 $_{Model}$			9 $_{Model}$		



Observations	415	418
Marginal R^2 / Conditional R^2	0.688 / 0.898	0.711 / 0.920
AIC	-866.420	
AICc	-865.644	

Table S20. CO_2 LUC (Mt CO_2e yr^{-1}) model summary. See Section 2.2.2 for additional information.

	CO_2 LUC (LMM)			CO_2 LUC (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	1714.86	1193.38 – 2236.33	**<0.001**	1741.58	1173.80 – 2309.36	**<0.001**
Delta pasture	416.20	362.29 – 470.11	**<0.001**	432.44	374.09 – 490.79	**<0.001**
Delta cropland	556.45	510.37 – 602.53	**<0.001**	611.27	563.51 – 659.04	**<0.001**
Delta afforestation	-128.94	-185.15 – -72.73	**<0.001**	-150.07	-209.67 – -90.46	**<0.001**
Carbon price	-393.74	-432.13 – -355.36	**<0.001**	-406.88	-447.59 – -366.17	**<0.001**
Year	-1595.71	-1634.26 – -1557.1	**<0.001**	-1609.46	-1650.27 – -1568.6	**<0.001**
Random Effects						
σ^2	1363770.78			1520109.12		
τ_{00}	1226381.08 Model			1383665.43 Model		
ICC	0.47			0.48		
N	18 Model			18 Model		

Observations	4729			4835		
Marginal R^2 / Conditional R^2	0.623 / 0.801			0.599 / 0.790		
AIC	80261.064					
AICc	80261.094					

Table S21. N_{fert} (LnR) model summary.

	N_{fert} (LMM)			N_{fert} (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.08	0.03 – 0.12	**0.001**	0.08	0.04 – 0.12	**<0.001**
$CropFeed_{rd}$ (%Δ)	0.06	0.05 – 0.08	**<0.001**	0.07	0.05 – 0.08	**<0.001**
$CropFeed_{m}$ (%Δ)	0.03	0.01 – 0.04	**<0.001**	0.03	0.01 – 0.04	**0.001**
$TotalSupply_{p}$ (%Δ)	0.09	0.09 – 0.10	**<0.001**	0.09	0.09 – 0.10	**<0.001**
Crop yields (%Δ)	0.02	0.01 – 0.03	**<0.001**	0.02	0.01 – 0.03	**<0.001**
NUE_{N} (%Δ)	-0.18	-0.19 – -0.17	**<0.001**	-0.18	-0.19 – -0.17	**<0.001**
N_{rec} (%)	0.00	-0.01 – 0.01	0.809	0.00	-0.01 – 0.02	0.761
Initial condition delta	0.03	0.01 – 0.06	**0.013**	0.04	0.01 – 0.06	**0.008**
Random Effects						
σ^2	0.01			0.01		
τ_{00}	0.00 Model			0.00 Model		
ICC	0.34			0.28		
N	9 Model			9 Model		
Observations	737			743		
Marginal R^2 / Conditional R^2	0.816 / 0.878			0.809 / 0.863		
AIC	-1388.418					
AICc	-1388.115					

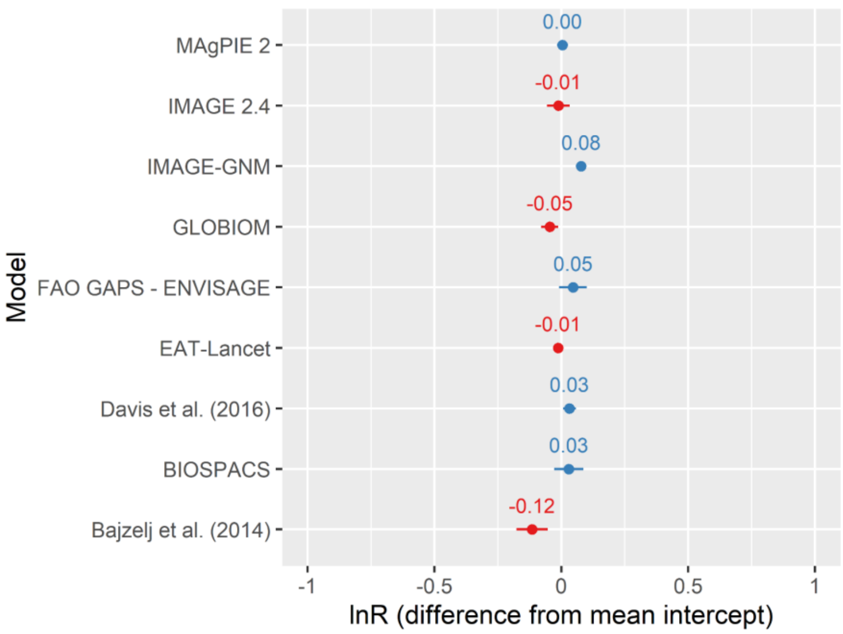
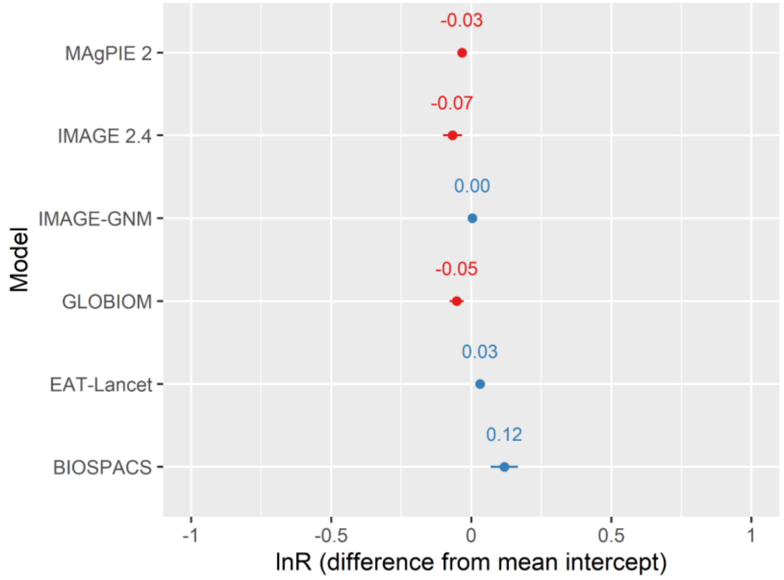


Table S22. $N_{surplus}$ (LnR) model summary.

	$N_{surplus}$ (LMM)			$N_{surplus}$ (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.01	-0.05 – 0.07	0.708	-0.00	-0.06 – 0.06	0.993
AllFeed$_{rd}$ (%Δ)	0.03	0.02 – 0.04	**<0.001**	0.03	0.02 – 0.04	**<0.001**
CropFeed$_{m}$ (%Δ)	0.10	0.08 – 0.11	**<0.001**	0.10	0.08 – 0.11	**<0.001**
TotalSupply$_{p}$ (%Δ)	0.09	0.08 – 0.09	**<0.001**	0.09	0.08 – 0.10	**<0.001**
Crop yields (%Δ)	-0.02	-0.02 – -0.01	**<0.001**	-0.02	-0.02 – -0.01	**0.001**
NUE$_{N}$ (%Δ)	-0.15	-0.15 – -0.14	**<0.001**	-0.15	-0.16 – -0.14	**<0.001**
Initial condition delta	-0.03	-0.04 – -0.01	**0.001**	-0.02	-0.04 – -0.00	**0.016**
Random Effects						
σ^2	0.00			0.00		
τ_{00}	0.01 Model			0.00 Model		
ICC	0.54			0.49		
N	6 Model			6 Model		



Observations	595	601
Marginal R^2 / Conditional R^2	0.848 / 0.931	0.845 / 0.921
AIC	-1476.236	
AICc	-1475.928	

Table S23. Pfert (LnR) model summary.

	Pfert (LMM)			Pfert (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.02	-0.08 – 0.04	0.460	-0.02	-0.07 – 0.03	0.408
$CropFeed_{rdm}$ (%Δ)	0.09	0.08 – 0.10	**<0.001**	0.09	0.08 – 0.10	**<0.001**
$TotalSupply_{p}$ (%Δ)	0.09	0.09 – 0.10	**<0.001**	0.10	0.09 – 0.10	**<0.001**
Crop yields (%Δ)	0.03	0.01 – 0.04	**<0.001**	0.03	0.01 – 0.04	**0.001**
NUE_{P} (%Δ)	-0.04	-0.05 – -0.03	**<0.001**	-0.04	-0.06 – -0.03	**<0.001**
N_{rec} (%)	-0.31	-0.32 – -0.31	**<0.001**	-0.31	-0.32 – -0.30	**<0.001**
Initial condition delta	0.01	-0.01 – 0.03	0.379	0.01	-0.01 – 0.03	0.403
Random Effects						
σ^2	0.01			0.01		
τ_{00}	0.01 Model			0.00 Model		
ICC	0.51			0.37		
N	8 Model			8 Model		
Observations	601			605		
Marginal R^2 / Conditional R^2	0.916 / 0.959			0.924 / 0.952		
AIC	-1303.060					
AICc	-1302.755					

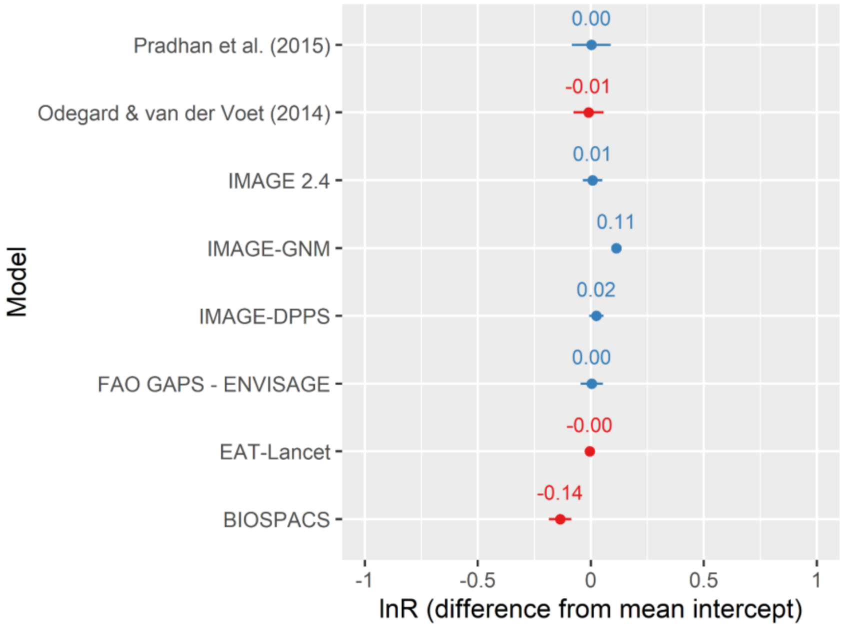
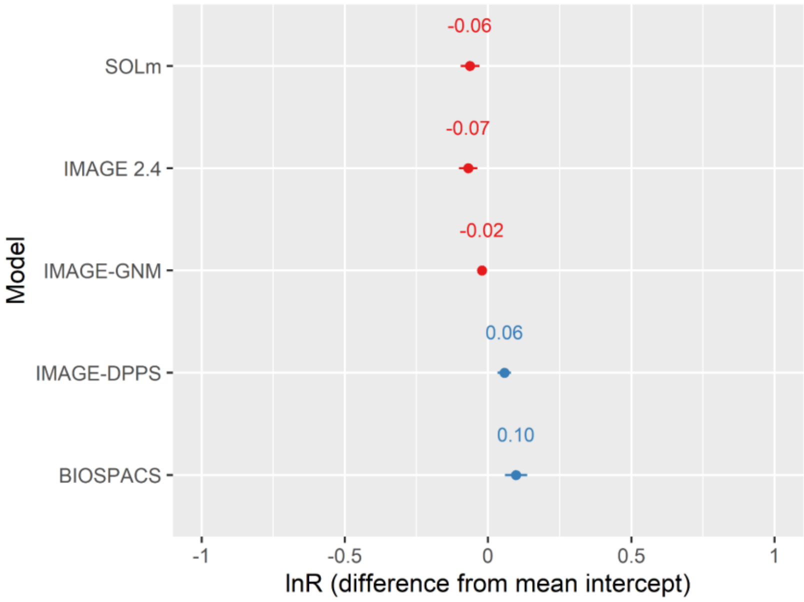


Table S24. $P_{surplus}$ (LnR) model summary. $P_{instream}$ is calculated from $P_{surplus}$ as described in Table S2.

	Psurplus (LMM)			Psurplus (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.20	0.12 – 0.28	<0.001	0.19	0.08 – 0.30	0.001
$GrassFeed_{rd}$ (%Δ)	0.04	0.01 – 0.07	0.002	0.06	0.04 – 0.08	<0.001
$CropFeed_{rdm}$ (%Δ)	0.11	0.09 – 0.13	<0.001	0.12	0.10 – 0.14	<0.001
$TotalSupply_{p}$ (%Δ)	0.01	-0.01 – 0.03	0.320	0.02	-0.00 – 0.03	0.080
Crop yields (%Δ)	0.06	0.03 – 0.08	<0.001	0.06	0.04 – 0.07	<0.001
NUE_{P} (%Δ)	-0.14	-0.15 – -0.13	<0.001	-0.14	-0.15 – -0.13	<0.001
N_{rec} (%)	0.01	-0.04 – 0.06	0.747	0.03	-0.03 – 0.09	0.349
Random Effects						
σ^2	0.00			0.00		
τ_{00}	0.01 Model			0.01 Model		
ICC	0.72			0.88		
N	5 Model			5 Model		



Observations	102			107		
Marginal R^2 / Conditional R^2	0.817 / 0.948			0.793 / 0.976		
AIC	-228.439					
AICc	-226.482					

2.4 Assumptions and limitations

2.4.1 Lack of spatially-explicit impacts

Our analysis focused on four planetary boundaries (land-system change, freshwater use, climate change, biogeochemical flows). These four boundaries and the 10 relevant environmental indicators selected to represent them (Section 1.2), were chosen due to their representation in the global food system scenario modeling literature, enabling adequate sample sizes for statistical analysis. Given the global scope of our analysis and the challenges entailed in extensive data collection from studies with disparate spatial and analytical modeling scopes, we only considered global environmental indicators. This did not account for spatially explicit planetary boundary transgressions and their impacts at the regional level (Section 1.2). For *TotalAgArea*, these were derived at the global level, without explicitly accounting for the three individual biomes of tropical, temperate and boreal forest (*17*). Not accounting for local or regional impacts underestimates exceedance risk across the spatially-dependent planetary boundaries of land-system change, freshwater use, and biogeochemical flows, with recent work focusing on adding regional granularity to the freshwater use (*41*) and biogeochemical flow (*262*) boundaries .

While our estimates of environmental limits encompassed wide uncertainty ranges incorporated in published estimates as well as the full range in potential future share of the global food system proxies for both overall boundary and regional uncertainty (Table S2), recent analyses highlight the added importance of process-detailed spatially explicit assessments to concurrently account for both local and global impacts (*31, 263*). Other work is also developing approaches to downscale planetary boundaries to the country-level (*30, 45, 264, 265*). A growing body of simulation results with harmonized country- and regional-level results from multi-model assessments (*97, 185, 266*), along with a better understanding of local biophysical thresholds and appropriate allocation methods, should enable more comprehensive risk-based assessments of future scenarios to be carried out at finer levels of spatial resolution.

2.4.2 Omitted planetary boundaries

As a result of our focus on specific boundaries, our analysis did not encompass the potential risk contribution of the food system on other environmental indicators and planetary boundaries. In addition to the four planetary boundaries explicitly quantified in our study, agriculture has been identified as a major contributor to impacts across other planetary boundaries including biosphere integrity, ocean acidification, stratospheric ozone depletion, and novel entities (*13*).

While land-system change control variables encompass elements of anthropogenic impact on biodiversity, biosphere integrity was not explicitly considered in our analysis. It is estimated that agriculture accounts for around 80% of total anthropogenic impact on the status of the biosphere integrity boundary, based on the assumption that genetic and functional diversity losses are primarily driven by land-use change (*13, 17, 267*). While a few recent assessments have modelled global food system impacts on extinction rates (*64*) and the biodiversity intactness index (BII) (*31, 263*), it was not possible for us to include biodiversity indicators due to very small study sample sizes. Given the continuing impact of population and agriculture in highly biodiverse locations such as the tropics (*103, 268*), in addition to the many strong interactions of biosphere integrity with other planetary boundaries (*269, 270*), not considering biodiversity impacts is likely to lead to an underestimation of risk of global food system futures. Also likely to be underestimated is the risk mitigation potential of interventions that reduce cropland/pasture expansion such as increases in crop yields, feed efficiency, and GHG mitigation through afforestation, as well as demand-side measures that reduce aggregate food demand.

As a major source of CO_2 emissions and nutrients from fertilizers to the world's oceans, agriculture is a major contributor to ocean acidification, estimated at 25% of total anthropogenic impact on this planetary boundary (*13*). No study identified during the systematic search contained estimates of future impacts of agriculture on ocean acidification, despite this having been specified in our search string (Search results were exported from ProQuest as spreadsheets and the percentage of test list articles retrieved in each search was assessed in order to optimize the search string. An initial 20% retrieval rate using ProQuest alone was improved to >50% when using the final search string. Ultimately an 80% retrieval rate (16/20 test list articles found) was achieved after search results from all four databases were combined (Data S2). No further refinements to the search string were made after this point to prevent a significant increase in the number of retrieved studies (over 5000) with little improvement to the overall retrieval rate of relevant articles. A total of 2548 studies (journal articles plus book chapters) were exported to Endnote for abstract screening (Fig. S1).

An anticipated challenge was to ensure adequate coverage of the grey literature given its importance in this research space (*21*). Further literature searches were conducted to retrieve relevant grey literature from reputable institutions using a simplified version of the final search string in the Google search engine. Further searches were conducted by adding a URL domain restriction such as those belonging to specialist organizations such as the FAO, World Bank, CGIAR, IFPRI, WRI, UNEP, UNCCD. A recent review article (*22*) was also used to identify additional reports from the grey literature. A total of 17 such reports were retrieved and exported to Endnote for further screening (Fig. S1).

Table S1). In a similar way as for biodiversity, the omission of ocean acidification from our analysis is likely to underestimate risk and the risk reduction achieved by measures that curb land-use change.

The use of chemical fertilizers and manure in agriculture has an impact beyond the biogeochemical flows boundary, contributing around 5% to stratospheric ozone depletion via the historical influence of chlorofluorocarbon emissions (*13*). However, as the major source of anthropogenic N_2O (currently the most potent ozone-depleting substance), it is expected to have much greater impact on ozone depletion in the future (*86, 211*). Another class of chemicals widely used in agriculture—pesticides—are encompassed in the novel entities planetary boundary (*17*). However, there is not yet an aggregate, global-level control variable or a planetary boundary value for novel entities. While abundant fertilizer and some pesticide estimates (*28, 271*) were available, it was not possible to relate these to explicitly quantify their impact on the planetary boundaries of ozone depletion and novel entities despite a general expectation that impacts from agriculture on these boundaries are likely to increase. We would assume that interventions such as nutrient-use efficiency and nutrient recycling would have a positive risk reduction impact on ozone depletion, while crop yield increases through conventional farming practices would likely entail significant trade-offs for both stratospheric ozone depletion and novel entities. Regenerative farming practices such as organic agriculture may also lead to reductions in risk for these planetary boundaries.

2.4.3 Unexplained variance in statistical models

The wide scope and statistical nature of our analysis meant that we were not able to encompass all possible interventions and predictors that are likely to affect each indicator. Several factors and dynamics acting at different spatial scales that could impact individual indicators have not been accounted for, as we were not able to obtain sufficient quantitative information across published studies to quantify them. Below is a list of potentially important aspects that we were not able to quantify but would expect, based on scenario storylines and the wider scientific literature, to account for some of the unexplained variance (related to marginal R^2 values for fixed effects) in our statistical models:

- *Grassland and pasture intensification*. This is an important productivity parameter for ruminants (*83*). While feed efficiency and food-competing feed account for some of the unaccounted-for variance, a dedicated pasture productivity variable would like improve the *Pasture* LMM fit.
- *Rainfed area contribution to production*. Expansion and improved efficiency and yields in rainfed areas is a key strategy for reducing water consumption in agriculture (*164, 205*). The water-use efficiency metric (Section 1.4.2) is supposed to control for this aspect as the denominator is total irrigated and rainfed production, meaning that higher yields in rainfed areas translates into a higher overall WUE thus reducing irrigation demand. This point is also related to aggregation bias due to not having enough data across papers to allow separate predictors for irrigated and rainfed yields (Section 2.4.4).
- *Land-use regulation and conservation actions*. Stricter regulation of land use is a key measure to limit total agricultural area and reduce GHG emissions (*272*), this is currently under-represented in most models (*97*). While this was partly accounted for through the use of a carbon price (Section 1.4.2), a more robust quantitative variable such as the area set aside for nature conservation, would have allowed explicit inclusion of this crucial parameter across the land-system change control variables.
- *Trade openness*. See discussion in Section 1.4.2.
- *Complex dynamics and non-linearity*. The assumption of linear responses between increased efficiency and mitigation across control variables is a limitation of our statistical approach. This is especially the case for Biogeochemical Flows where nutrient-use efficiency has a non-linear relationship with $N_{fert}/N_{surplus}$ because of the possibility of declining spatial efficiency of N across regions, as has been historically observed (*180, 273*). Similarly, complex non-linear dynamics impact on stocks of residual soil phosphorus stocks in cropland and negative soil phosphorus budgets (deficits) in intensively grazed grasslands (*93*), meaning that an assumed linear relationship between nutrient-use efficiency and $P_{fert}/P_{surplus}/P_{instream}$ may be an oversimplification.

2.4.4 Aggregation bias

Due to the global scope of the analysis, we calculated weighted global averages of several regionally or sectorally disaggregated parameters which introduced aggregation bias. The following are key sources of bias and their likely effects on the results:

- *No distinction between rainfed and irrigated yields*. It is well known that yields differ between rainfed and irrigated agriculture, with significantly higher yield gaps and opportunities for improvement in rainfed areas (*161, 164*). However, this level of disaggregation was not available across most studies.

- *No distinction between different monogastric products*. Eggs, chicken, pork, and aquaculture differ widely in environmental impact but the models were not of sufficient fidelity to explicitly capture this nuance (*82*).
- *No explicit modelling of the effects of regional trends in agricultural productivity, population, income growth and urbanization on food demand and environmental risk.* All projections and risk estimates presented in the analysis are global totals. This ignores potentially diverging trends across different regions due to the complex interplay of the aforementioned drivers (*103, 274, 275*). However, such regional dynamics are incorporated into the storylines and weighted global averages of the quantitative variables used as inputs to the meta-regression models.
- *Incomplete set of intervention combinations*. To limit scenario numbers and computational challenges, interventions such as reductions in animal calories or feed efficiency were applied uniformly across livestock types. While the chosen intervention levels ensure consistency by reflecting the range in the published literature, different animal-source foods have highly diverse environmental effects (*82*). Our models use different predictor variables for ruminant meat (beef and lamb), dairy, and monogastric products (pork, chicken, eggs, and aquaculture) to capture such effects. It is therefore likely that there are more intervention level combinations than those identified that meet risk thresholds (e.g., through further reductions in ruminant meat and concomitant increases in dairy or monogastric products). This would allow exploring more desirable or feasible combinations suited to different geographic and socio-cultural settings (*276*).

2.5 Additional meta-model results

2.5.1 Base year and BAU projections

Table S25. Base year and BAU projections for 2050 across all planetary boundary indicators. BAU estimates assume that population, diet (animal and plant calories), waste, crop yields, feed efficiency (FCR) and feed composition will follow recent trends while climate action, water-use efficiency, nutrient-use efficiency, and nutrient recycling will remain at low (current) levels of ambition.

		Base year (2010)		Trend - All intervention settings (2050)		
Planetary boundary	**Indicator**	**Units**	**Mean estimate**	**Mean projection**	**Standard deviation**	**Risk of exceedance**
Land-system change	Cropland	Mha	1520[a]	2013	155	-
	Pasture	Mha	3277[a]	3413	516	-
	Total agricultural area	Mha	4797	5427	538	0.97
Climate change	Methane	Mt CO_2e yr^{-1}	3659[b]	4676	229	-
	Nitrous oxide	Mt CO_2e yr^{-1}	1964[b]	2592	209	-
	Land-use change	Mt CO_2e yr^{-1}	4900[c]	3567	1177	-
	Total direct agriculture emissions	Mt CO_2e	10523	10835	1226	0.98
Freshwater use	*Blue water consumption*	km^3 yr^{-1}	1807[d]	2793	190	0.72
Biogeochemical flows – N	Nitrogen fertiliser	Tg yr^{-1}	103.7[e]	167.9	14.6	1.00
	Nitrogen surplus	Tg yr^{-1}	134.4[f]	201.0	14.3	1.00
Biogeochemical flows – P	Phosphorus fertiliser	Tg yr^{-1}	17.9[e]	29.6	2.39	1.00
	Phosphorus instream	Tg yr^{-1}	4.76[g]	5.34	0.76	1.00

[a] FAOSTAT Land Use Domain (*48*)
[b] FAO Tier 1 IPCC Agriculture using AR6 GWP-100 factors (*251*)
[c] UNFCC mean annual GHG flux for 2000–2010 from land use and land-use change (*277*)
[d] Springmann et al. (2018) (*19*)
[e] FAOSTAT Fertilizers by Nutrient (*278*)
[f] Willet et al. (2019) (*64*)
[g] Beusen et al. (*92*)

2.5.2 Mitigation barplots for all indicators across intervention levels

This section presents mitigation potentials for each of the 10 environmental indicators across all intervention levels, estimated using the statistical meta-regression models (Section 1.4). These results complement here in terms of percentage increase complement the exceedance risk presented in the main manuscript.

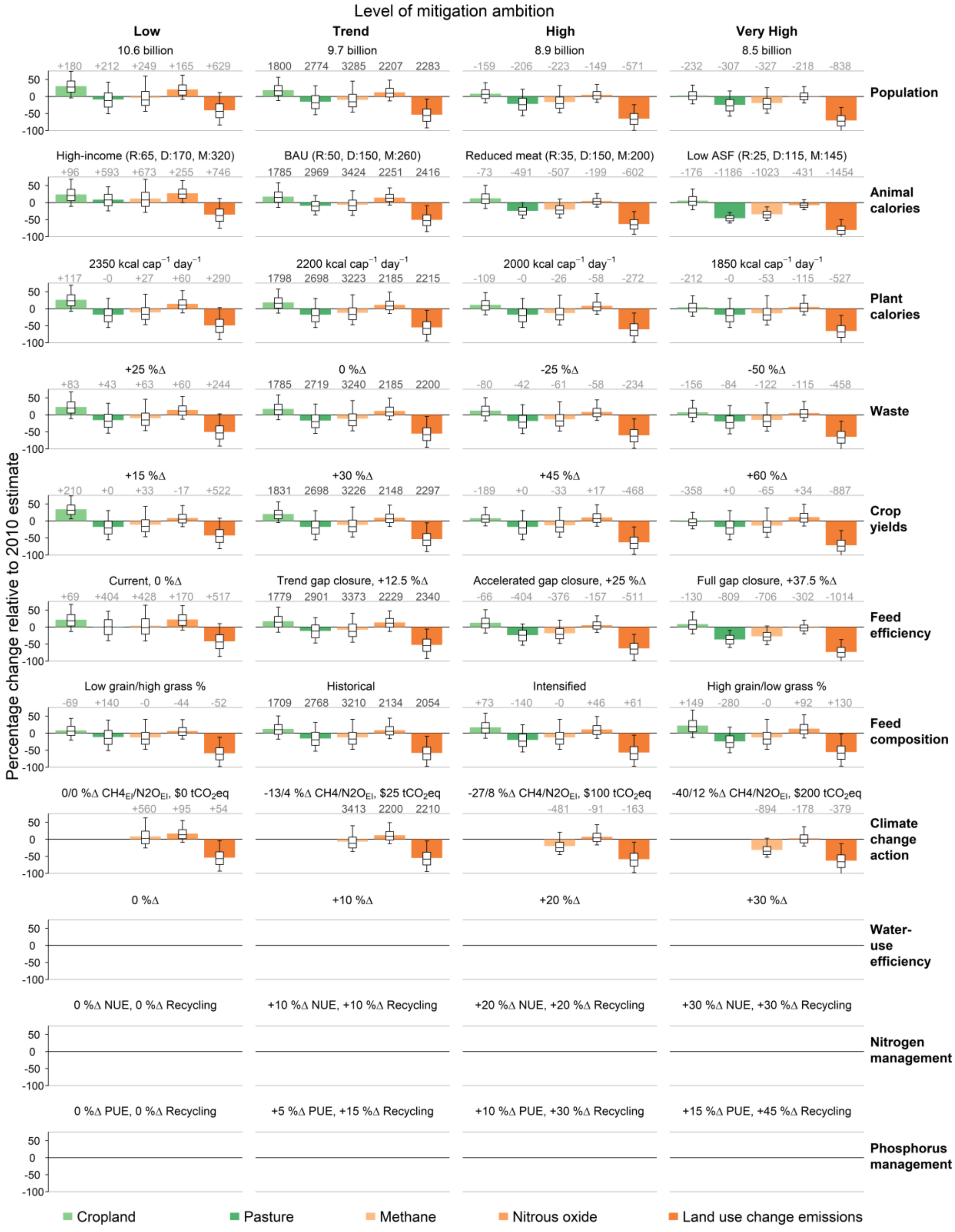


Fig. S4. Modeled effect size (percentage deviation relative to 2010 base year) values for all Land-System Change and Climate Change indicators under a range of settings for the 8 relevant interventions. Each bar/boxplot presents the distribution of projection estimates for all levels of mitigation ambition across all other interventions. Bars denote mean percentage deviation, boxes denote median and 25th/75th percentiles, and whiskers denote 5th/95th percentiles [see Data S4 for full dataset. Dark/light grey text above bars indicates mean values (Mha for Cropland/Pasture, Mt CO_2e yr^{-1} for CH_4/N_2O/LUC based on AR6 GWP-100 factors) for mean trend setting and deviation relative to Trend for all other columns. Missing bars correspond to interventions excluded from individual models due to lack of relevance, adverse impacts on model performance, collinearity, or missing/insufficient data. [R= ruminant meat, D = dairy, M = monogastric protein including aquaculture and eggs, all calories are expressed in food intake terms, with the 0% waste setting being equivalent to food supply in FAOSTAT Food Balance Sheets (*142*) assuming current rates of retail and household waste (*19*, *155*)].

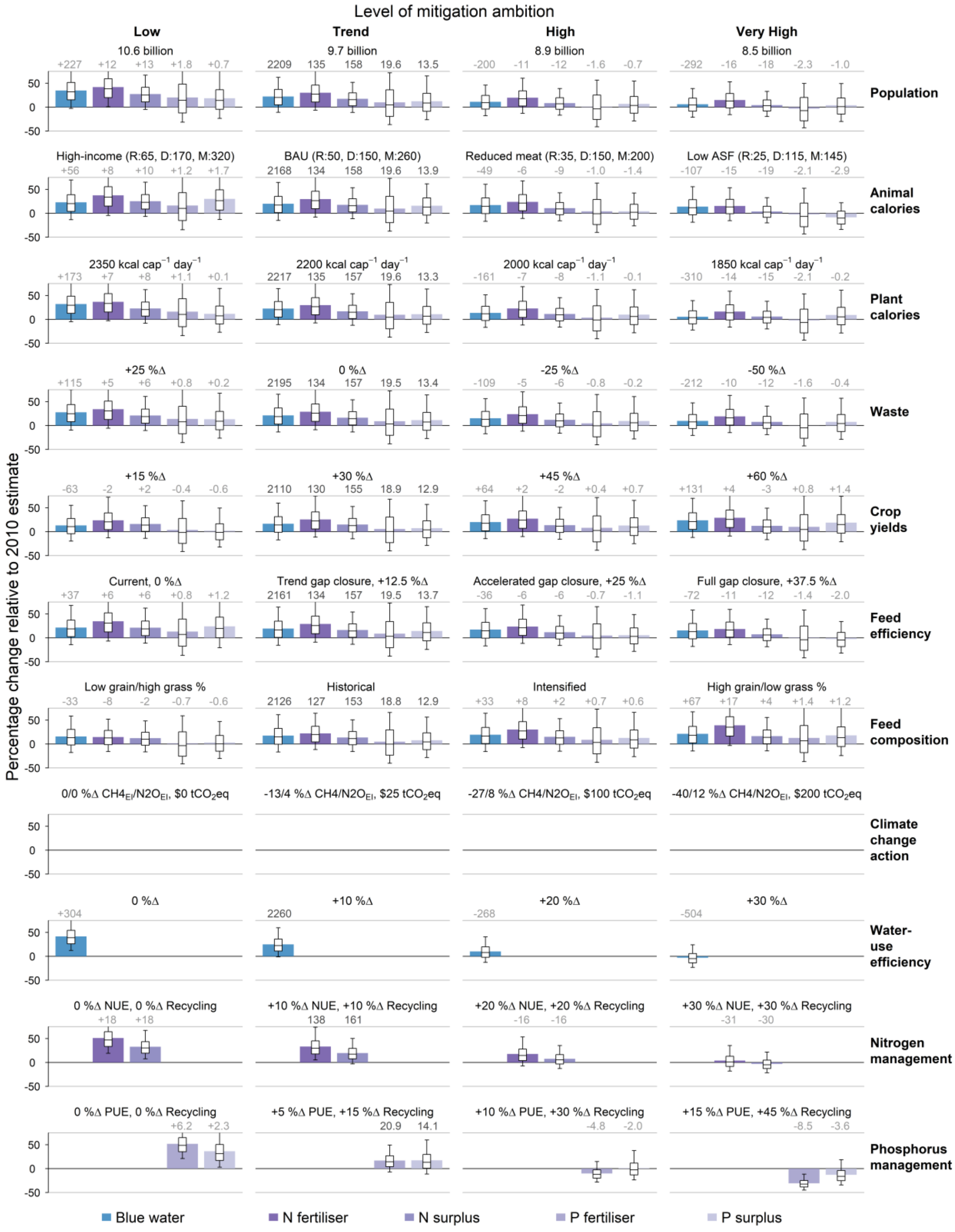


Fig. S5. Modeled effect size (percentage deviation relative to 2010 base year) values for all Land-System Change and Climate Change indicators under a range of settings for the 10 relevant interventions. Each bar/boxplot presents the distribution of projection estimates for all levels of mitigation ambition across all other interventions. Bars denote mean percentage deviation, boxes denote median and 25th/75th percentiles, and whiskers denote 5th/95th percentiles [see Data S4 for full dataset. Dark/light grey text above bars indicates mean values (km^3 yr^{-1} for blue water consumption, Tg P/N yr^{-1} for N/P fertilizer and surplus) for mean trend setting and deviation relative to Trend for all other columns. Missing bars correspond to interventions excluded from individual models due to lack of relevance, adverse impacts on model performance, collinearity, or missing/insufficient data. [R= ruminant meat, D = dairy, M = monogastric protein including aquaculture and eggs, all calories are expressed in food supply terms compatible with FAOSTAT Food Balance Sheets (*142*), assuming current rates of retail and household waste (*19*, *155*)].

2.5.3 Final mapping of risk-compliant combinations

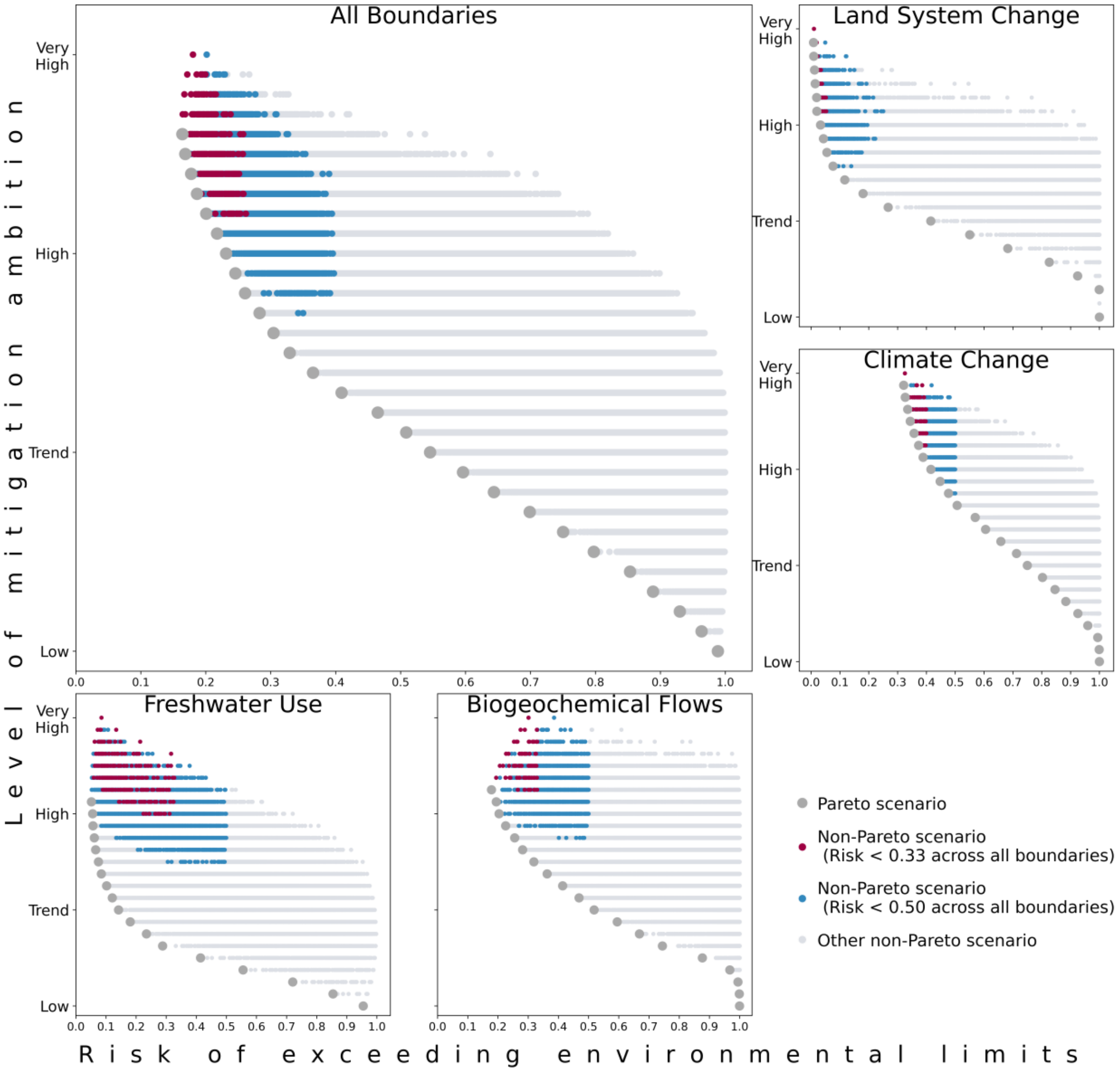


Fig. S6. Trade-offs between average mitigation ambition and risk reduction for all boundaries. Shown are the combined Pareto front which assumes equal-priority weighting of all four boundaries (large panel, n = 2,097,152), and Pareto fronts for each planetary boundary (smaller panels, where $n = 4^7 =$ 16,384 for land-system change, $n = 4^8 = 65{,}536$ for climate change, $n = 4^8 = 65{,}536$ for freshwater use, and $n = 4^8*2 = 131{,}072$ for biogeochemical flows. Pareto sets (dark grey circles) represent the most efficient (non-dominated) scenarios where trade-offs between the objectives of risk reduction and level of mitigation ambition, both of which should ideally be kept as low as possible, are minimized. Any additional risk reduction (moving left along the x-axis) is possible at the given level of mitigation ambition (y-axis), or vice versa, where the same risk reduction cannot be achieved with a lower level of mitigation ambition. Based on IPCC calibrated uncertainty language (*250*), blue dots denote the scenarios with < 0.50 risk (*exceedance about as likely as not*) across all boundaries while the red dots are the subset of scenarios with < 0.33 risk (*exceedance unlikely* – for climate change this threshold is set to 0.40). The clouds of light grey dots are all the scenarios that do not belong to the Pareto set and also exceed the 0.5 condition for at least one planetary boundary.

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