Ambitious food system interventions required to mitigate the risk of exceeding Earth's environmental limits

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SUMMARY

Transforming the global food system is necessary to avoid exceeding the Earth's environmental limits. 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 an evidence synthesis of global food system modeling studies, to quantify the potential of individual and combined interventions to mitigate the risk of exceeding global environmental limits for agricultural area, greenhouse gas (GHG) emissions, surface water flows, and nutrient cycles by 2050. GHG emissions and nutrient cycles are the most difficult limits to avoid exceeding, and are conditional on shifts towards diets with a low proportion of animal-source foods, steep reductions in emissions intensity, substantial improvements in nutrient management, feed conversion ratios and crop yields, and efforts to limit overconsumption and food waste. Ambitious actions across the global food system are required to ensure the required level of risk mitigation.

INTRODUCTION

The global food system is pushing environmental indicators 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 [5,6]. Business-as-usual (BAU) scenarios of global food production and consumption to 2050 are almost certain to exceed several planetary boundaries [7-12], 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 (mitigation options) that can facilitate this transformation [13-17], a comprehensive and integrated assessment of the scale and combination of interventions that can keep the Earth system within environmental limits is urgently required to support policy making and catalyze on-ground action.

Over the past decade, global studies have presented many scenarios and estimates of the environmental benefits of a range of demand-side and supply-side food system interventions. However, the outputs and conclusions are sensitive to several analytical choices, including the modelling paradigm; input data and model parameterization; scenario specification; type and scale (or *ambition*) of interventions assessed; and the environmental indicators used [18-20]. These choices are influenced by study aims and researcher worldviews [21,22], leading to bias and gaps in our understanding of the environmental impacts of food system trajectories and the effectiveness of interventions. The recent criticism[23] of the FAO's 1.5 °C roadmap [24], which found a low mitigation potential for dietary change (at odds with recent studies [12,25,26]), demonstrates how preferential data and scenario choices could potentially misinform policy. Intercomparisons of land-use change [18,20,27,28] and selective reviews of other environmental indicators [15,29,30] highlight the considerable range in 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 thresholds that define global environmental limits (such as planetary boundaries or Earth system boundaries) are often set conservatively to avoid exceeding biophysical tipping points [1,2,4,5,31] and include a zone of uncertainty that accounts for incomplete scientific knowledge and variability in Earth system functioning [32,33]. 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 [7,8]. Given these uncertainties, a risk assessment framework that reflects the latest scientific consensus can enhance the evaluation of food system interventions by determining the probability or *risk* of exceeding environmental limits.

Here, we present a synthesis of 64 global food system modeling studies. Our quantitative analysis is underpinned by an input database with thousands of scenario projections from a curated subset of studies to identify the effects of various interventions, and the combinations that keep the Earth's system within a safe operating space by 2050. We developed a quantitative risk assessment framework underpinned by a suite of statistical *meta-regression* models that estimate the risk mitigation potential of major food system interventions relating to four global environmental limits: agricultural area, GHG emissions, surface water flows, and nutrient cycles. These are defined by the latest consensus on global environmental limits, notably research on planetary boundaries (PBs)[4] and Earth system boundaries (ESBs)[5]. The approach controls for a wide range of model sensitivities and uncertainties. Our analysis delivers comprehensive risk mitigation estimates for individual interventions and explores intervention combinations and key on-ground actions that can help move the food system within environmental limits.

RESULTS

Synthesizing available evidence and quantifying risk

We systematically reviewed modeling studies of the global food system published in academic journals and major international reports since the year 2000, with environmental impact estimates up to and including 2050. Out of the 1,688 studies originally identified, we used a robust protocol to select 64 for further qualitative and quantitative synthesis (Note S1; Fig. S1). For the quantitative analysis we assembled a harmonized dataset (Data S1) of projected future food system impacts for eight environmental indicators that relate to four key environmental limits (Note S2), based on a subset of 26 studies (Fig. 1a). The scope of our review includes terrestrial crop and livestock systems and 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 [19]. Intervention scenarios range from marginal to substantial deviations from the BAU [34], based on a range of supply-side and demand-side interventions that can reduce environmental impacts (Note S3). *Supply-side interventions* include improved farm management, increased efficiency, and technological advances that can reduce resource use and emissions [35,36] (e.g., yield gap closure in crop and livestock systems, or more fundamental agronomic interventions such as changes in feed composition). *Demand-side interventions* include a range of socio-cultural and technological changes that can decrease or alter aggregate food demand, namely a slowdown in the population growth rate, shifts towards more plant-based diets, and reductions in food waste [37-40].Typically, studies either assess just a single intervention or scenario narratives integrating multiple interventions, such as the shared socioeconomic pathways (SSPs) [20,28]. 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.

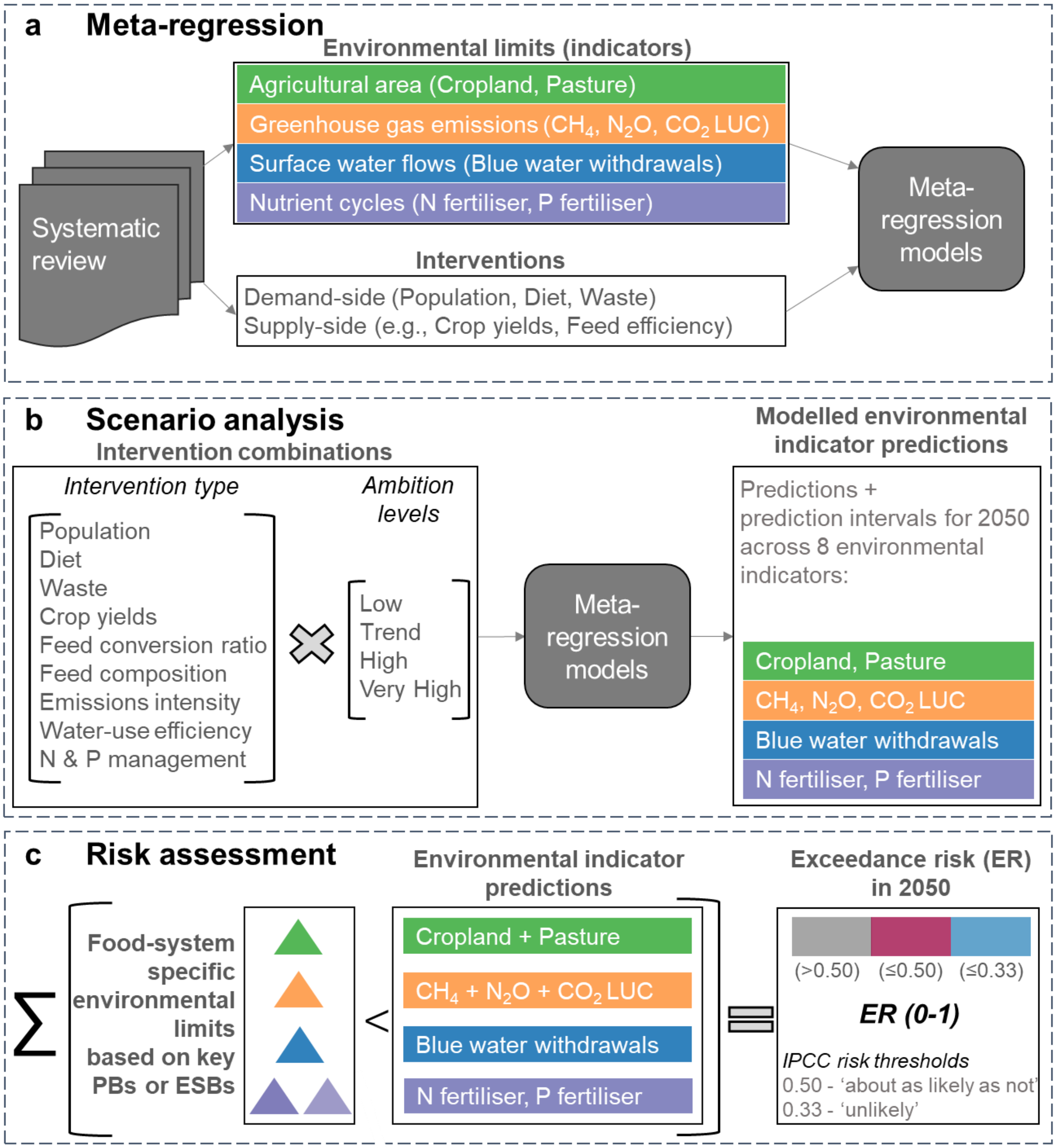

Fig. 1. Intervention modeling and risk assessment framework. A simplified illustration of the three main stages of the analysis. **a.** Linear mixed effects meta-regression models for eight environmental indicators corresponding to four key environmental limits (agricultural area, GHG emissions, surface water flows, nutrient flows), and intervention-related variables extracted from selected studies. **b.** Database with mean predictions and prediction intervals for each of the eight environmental indicators comprising all relevant intervention combinations (Table 1). **c.** Exceedance risk calculation combining environmental limit probability density functions (Table 2, Table S2) and meta-regression model prediction intervals. [PB = planetary boundary, ESB = earth-system boundary, LUC = land-use change, N = nitrogen, P = phosphorus]. For the N and P cycles, risk estimates were calculated separately and then averaged to derive a nutrient cycle risk metric.

To enable a quantitative synthesis of food system interventions, we identified eight key environmental indicators representing the four critical environmental limits of agricultural area, GHG emissions, surface water flows, and nutrient flows (Table 1; Note S2). We then selected and harmonized a set of quantitative variables representing major interventions (Table 2; Note S3). We used the compiled data from the selected food system models to fit linear mixed-effects meta-regression models for each of the environmental indicators, with interventions modelled as composite fixed effects predictor variables, and with the effect size (environmental impact relative to the base year) as the dependent variable (Note S4). We established four levels of mitigation ambition (Low, Trend or BAU, High, and Very High) for each intervention for 2050, based on the range in the scale of implementation considered across the reviewed studies or recently published projections (Table 2). Using the meta-regression models, we generated predictions for all combinations of relevant intervention levels against each environmental indicator for 2050 (Fig. 1b). Following a sensitivity analysis protocol[20], we used our prediction database to compute individual effects for each intervention level relative to the Trend.

Table 1. **Food-system specific environmental limits for selected environmental indicators in 2050.** Includes best estimate (mode), lower bound (minimum), and upper bound (maximum). In italics are the additive indicators used to assess risk against the food-system specific share of relevant planetary boundary (PB) or Earth system boundary (ESB). For detailed methodology and full list of data sources see Note S2; Table S2.

Indicator **(sub-indicator)**	**Abbreviation**	**Environmental limit best estimate (low – high estimate)**	**Relevant global PB or ESB**	**Short description**
Sum of the area of all arable land and land under permanent crops	Cropland		Land-system change	Total land area under agriculture (cropland + pasture) adjusted for possible pathways in non-agricultural uses (mining, infrastructure, and urban expansion), compatible with the 54-75% (3466-4790 Mha) global forest cover requirement across major forest biomes (tropical, temperate, boreal)[2,4].
Area under permanent meadows and pastures	Pasture			
Total agricultural area (i.e., cropland + pasture)	*TotalAgArea*	<3.31 (3.20 – 5.46) billion ha		
Direct on-farm CH_4 emissions	CH_4		Climate change	Total agriculture emissions (direct CH_4 + N_2O + net CO_2 emissions from land use and land-use change) in line with the published range of estimates of agriculture's share of the global carbon budget in vetted IPCC AR6 scenarios consistent with staying within 2.0 and 1.5 °C[36,41].
Direct on-farm N_2O emissions	N_2O			
Land-use change CO_2 emissions	CO_2LUC			
Direct GHG emissions from agriculture (i.e., CH_4 + N_2O + CO_2*)*	*NonCO_2+LUC*	<2.67 (-3.87 – 11.0) Gt CO_2e yr^{-1}		
Water withdrawals (surface water and groundwater) by agriculture	*Water*	<4,400 (1,033 – 8,558) $km^3\,yr^{-1}$	Surface water flows	Total blue water withdrawals in agriculture adjusted for possible pathways in water demand across other economic sectors and relative future contributions of surface water and groundwater[42]. Safe withdrawal limits were computed as globally aggregated environmental flow requirements based on flow alterations no greater than 15% (10-20%) for maintaining moderate to high levels of ecological protection in riverine ecosystems[5,43].
Total synthetic nitrogen fertiliser application in agriculture	N_{fert}	<69 (52 - 113) Tg N yr^{-1}	Nutrient cycles: Nitrogen	Safe thresholds for N_{fert}, and P_{fert} based on the latest consensus in global environmental limits[4,5,8]. The N_{fert} limits exclude biological fixation as per [8]. No cumulative boundary was possible due to the non-additive nature of the individual indicators. Instead, risk estimates were averaged across indicators to derive risk metrics.
Total mined phosphorus fertiliser application in agriculture	P_{fert}	<16.0 (6.0 – 17.0) Tg P yr^{-1}	Nutrient cycles: Phosphorus	

Table 2. Intervention levels and combinations. Includes the levels of mitigation ambition for each intervention with examples of mitigation actions, as synthesized from selected studies (see Data S3 for full list of actions). Relevant environmental limits are those where we assume an intervention to have a significant impact (Note S4). [ASF = animal-source foods, DM = dry matter, FCF = food-competing feed, EI = GHG intensity, NUE = nutrient-use efficiency].

Interventions		Level of mitigation ambition: Low	Trend	High	Very High	Units	*Description*. Mitigation action example.	Relevant limits
Demand-side								
Population		10.1	9.66	9.5	9.1	Billion people	*Global human population in 2050 according to the latest median estimate by the United Nations [44] and the range across SSP 3.0 scenarios [45].* This intervention could be enabled through reducing fertility rates via promoting education and reproductive health services [40,46].	All
Diet							*Global daily average calorie intake from 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 [39]. All combinations between animal and plant calories are modelled *ceteris paribus* and 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 [8] and meets the World Health Organization recommended vitamin B_{12} intake of 2.4 µg day^{-1} for adults and adolescents [47]. Values >2400 kcal cap^{-1} day^{-1} are considered representative of overconsumption in predominantly sedentary high-income populations [48] (see Table S8;Table S10).	All
Animal calories		Rich	BAU	Low meat	Low ASF	kcal cap^{-1} day^{-1}		
Ruminant meat		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}		
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 education and awareness campaigns or reductions of serving sizes [49] (see Table S11).	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) [50].	All
Feed conversion ratio						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 [51] (see Table S12).	All
Ruminant meat		35	30	25	20			
Dairy		2	1.75	1.5	1.25			
Monogastric		4	3.5	3.0	2.5			
Feed composition						% 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 interacts with feed conversion ratios and can involve either increasing the amount of feed from ecological leftovers (i.e., grass, food waste, by-products) and/or the use of degraded/abandoned land [22], or intensification of livestock production in feedlots (see Table S13).	All
Ruminant meat		5	10	15	20			
Dairy		15	20	25	30			
Monogastric		80	85	90	95			
GHG 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 [52].	GHG emissions
	EI_{N2O}	0	4	8	12	%Δ		
	Carbon price	0	25	100	200	US$2010 t CO_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 soil carbon farming practices [14,35].	
Water-use efficiency		0	5	10	15	%Δ	*Increase in crop yield relative to the volume of water withdrawn (in kg of crop relative to blue water withdrawals 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 [53,54].	Surface water flows
N & P management								Nutrient cycles
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 [55]. For N the Very High setting corresponds to an increase from a global 2010 average NUE_N of 0.46 [56] to 0.60 by 2050. For P this corresponds to a change from 0.67 [10,57] to 0.78 in 2050.	
	NUE_P	0	5	10	15	%Δ		
Nutrient recycling	N	0	10	20	30	%	*The proportion of synthetic nitrogen or mined phosphorus fertiliser offset through recycling of agricultural and human waste streams.* This intervention follows the formulation in [8,58] and entails improvements in infrastructure (pit latrines, septic tanks, enhanced sewage systems) to enable the recycling of nutrients from agriculture (manure and crop residues) and human waste (household waste and sewage) [55,57].	
	P	0	15	30	45	%		

We then defined triangular probability density functions (PDFs) capturing the best estimate and uncertainty zone for each environmental limit (Table 1, Table S2). Following principles of probabilistic risk assessment [59], the risk of exceeding relevant limits for each modelled indicator prediction was calculated by comparing Gaussian distributions drawn from modelled prediction intervals against PDFs of environmental limits (Fig. 1c, Fig. S2). By pooling risk estimates for all environmental limits, we identified combinations of intervention levels that remained below two critical IPCC risk thresholds for describing quantified uncertainty [60,61]: < 0.50 risk (exceedance *about as unlikely as not*) and < 0.33 risk (exceedance *unlikely*) (Note S4). We finally complemented the quantitative synthesis with a qualitative review of the 64 systematically selected studies to identify tangible real-world actions that could enable the levels of ambition required across all modelled demand- and supply-side interventions.

The location of key risk thresholds differs by indicator and risk level

The shapes of triangular PDFs of environmental limits in 2050 reflect the level of uncertainty around minimum and maximum estimates (Table 1; Note S2). This impacts the location of different risk thresholds in relation to the best estimate (Fig. 2). While previous research[8,49] implicitly considers values below the best estimate as representative of a more acceptable level of risk, depending on the nature of the distribution, the best estimate may still entail an elevated level of risk relative to one or both critical IPCC risk thresholds (0.33 and 0.50). For example, in the case of agricultural area (Fig. 2a), a distribution with a mode (best) estimate (3.31 billion ha) very close to the minimum (3.20 billion ha) means that both the 0.50 and 0.33 risk thresholds are substantially higher than the best estimate. The opposite is the case for phosphorus (Fig. 2e), where the mode (best) estimate of 16 Tg P yr^{-1} is close to the maximum (17 Tg P yr^{-1}), and is therefore higher than both risk thresholds. In the cases of GHG emissions (Fig. 2b) and water withdrawals (Fig. 2c) where the triangular distribution is more symmetric, the best estimate lies in between the two risk thresholds, while for nitrogen (Fig. 2d) the best estimate directly overlaps with the 0.33 risk threshold.

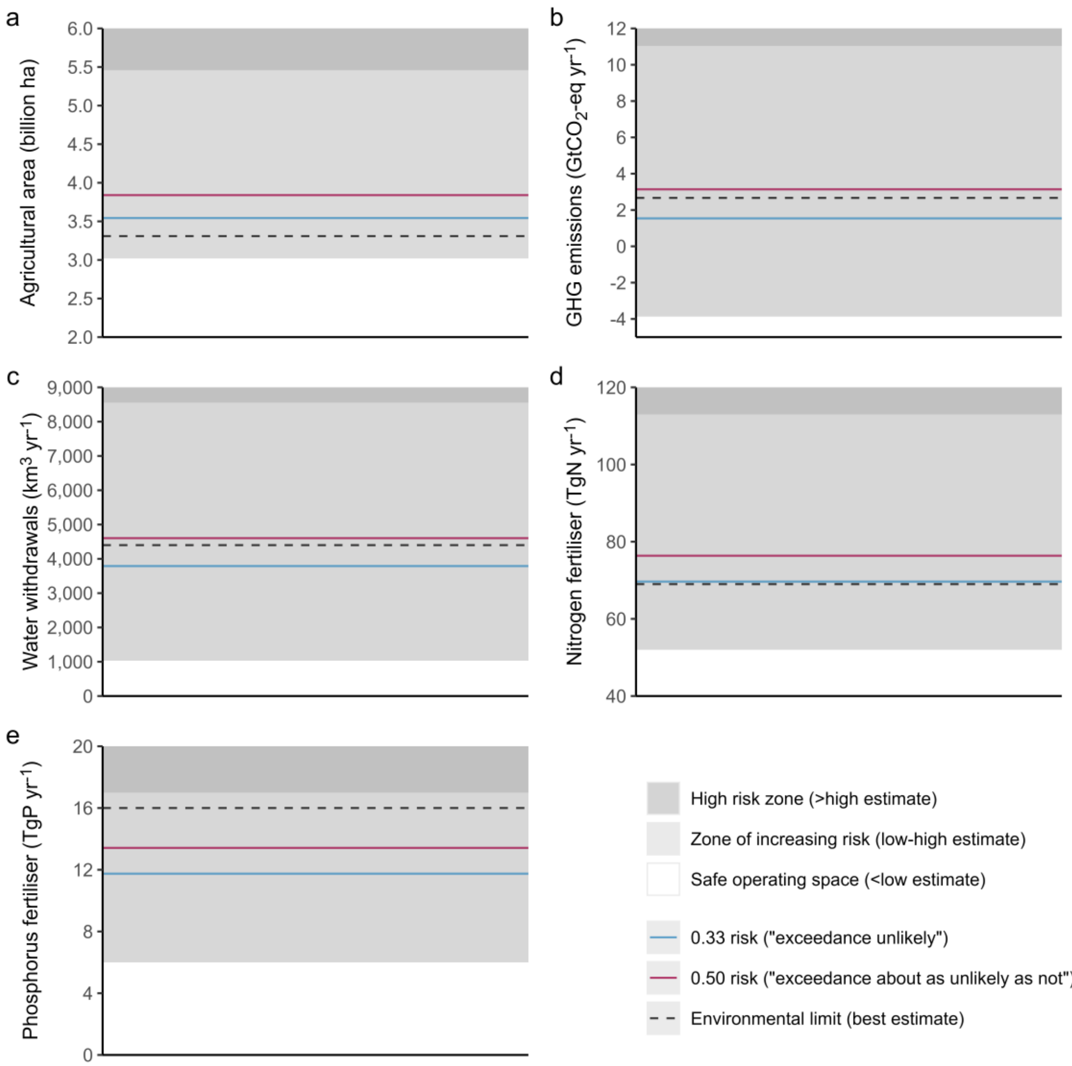

Fig. 2. Critical risk thresholds and risk zones for each environmental indicator/limit in 2050. Shaded areas represent the different risk zones following planetary boundary terminology [2,4]. Blue and red horizontal lines represent two IPCC risk thresholds (0.33 and 0.50) and the dashed black line is the best estimate (mode) of the environmental limit (see Table 1).

Mitigation potential of individual food-system interventions

We present modelled predictions of mitigation potential for individual interventions set at different levels of mitigation ambition relative to the TREND (all interventions set at Trend level) in 2050 (Fig. 3; see Fig. S4 for sub-indicator results). To illustrate the results in the sections below, we concentrate on the mean maximum mitigation potential (Very High relative to TREND) expressed as a percentage reduction relative to the TREND prediction and as reduced pressure in physical units.

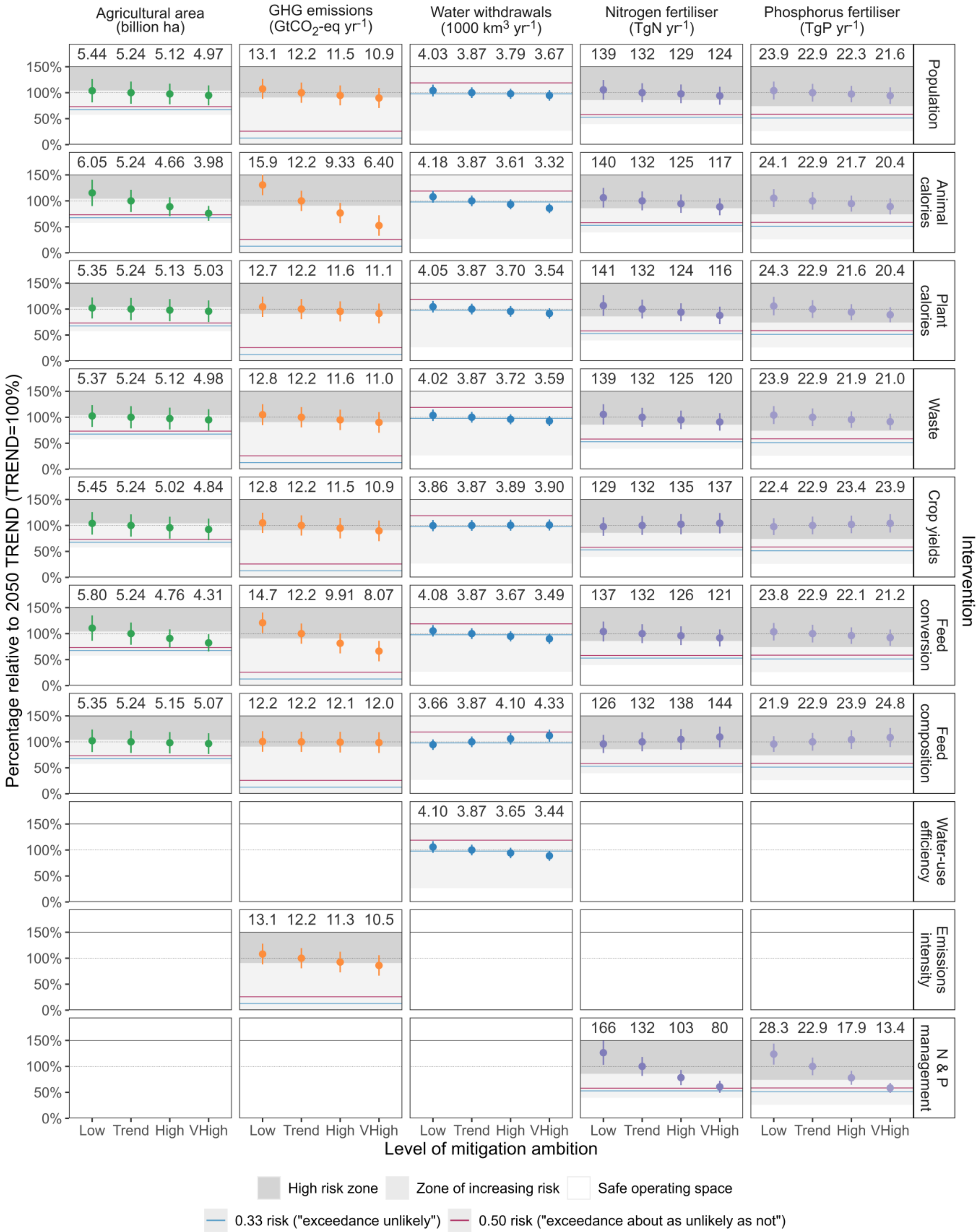

Fig. 3. Modeled mitigation potential in 2050 under a range of ambition levels for selected interventions. Each panel presents percentage impact relative to the 2050 TREND baseline (all interventions at Trend level) for a specific level of mitigation ambition (x-axis) of a selected intervention (facet rows), across each of the environmental indicators (see Table

1). Data are presented as mean predictions (bubbles) and 95% bootstrap prediction intervals (vertical lines). Black numbers at the top of panels indicate pressure in physical units (e.g. billion ha for agricultural area). Shaded areas represent the different risk zones following planetary boundary terminology [2,4]. Blue and red horizontal lines represent the two IPCC risk thresholds (0.33 and 0.50). Empty panels correspond to interventions excluded from individual models due to lack of relevance, or missing/insufficient data. See Note S7 for sub-indicator results and Data S4 for source data.

Demand-side interventions show significant mitigation potential across all indicators

Demand-side interventions show high mitigation potential across all indicators, with some variability depending on the indicator (Fig. 3). Shifting to diets with a low proportion of animal-source food (Very High ambition) could achieve the maximum risk reduction across agricultural area (-24.0%; -1.26 billion ha) and GHG emissions (-47.4%; -5.77 $GtCO_2eq$), reflecting reduced demand for pasture and feed crops and reduced GHG emissions from enteric fermentation (Fig. S4). A low animal-source food (ASF) diet also shows considerable mitigation potential for water withdrawals (-14.2%; -550 km^3), and nutrient flows (-11.4% N_{fert}, -10.8% P_{fert} ; -15.0 Tg N_{fert}, -2.48 Tg P_{fert}). Other demand-side interventions also result in substantial mitigation potential across all indicators, especially for GHG emissions (-10.3%; -1.25 $GtCO_2eq$ for population interventions) and nutrient flows (-12.2% N_{fert}, -11.0% P_{fert} ; -16.0 Tg N_{fert}, -2.52 Tg P_{fert} for plant calorie reduction) (Fig. 3).

Among supply-side interventions, improvements to feed conversion ratios have the highest overall mitigation potential across all indicators, with an especially strong effect on agricultural area (-17.7%; -0.93 billion ha) and GHG emissions (-33.6%; -4.09 $GtCO_2eq$) owing to substantially reduced feed demand from both cropland and pasture (Fig. 3; Fig. S4). Targeted interventions such as water-use efficiency, reductions in emissions intensity, and N&P management, show considerable mitigation potential for each of the relevant indicators. Unlike GHG emissions and agricultural area, supply-side interventions such as improved N&P management show much higher mitigation potential for nutrient flows (-39.2% N_{fert}, -41.5% P_{fert} ; -51.7 Tg N_{fert}, -9.52 Tg P_{fert}) due to their strong influence on improving nutrient use efficiency and recycling. Improvements in water-use efficiency have a slightly lower effect compared to a low ASF diet on water withdrawals (-11.1%; -430 km^3).

Some supply-side interventions exhibit trade-offs across certain indicators

Actions to increase crop yields and change feed composition have trade-offs for some indicators (Fig. 3). Higher (+60%, Very High ambition) crop yields have considerable mitigation potential for agricultural area (-7.6%; -0.40 billion ha) and associated GHG emissions (-10.4%; -1.26 $GtCO_2eq$), because of avoided cropland expansion and forest regrowth substantially outweighing the increase in N_2O emissions from additional fertilization (Fig. S4). However, higher crop yields could slightly increase water withdrawals (+0.8%; +30 km^3) and nutrient flows (+4.3% N_{fert}, +4.1% P_{fert} ; +5.70 Tg N_{fert}, +0.94 Tg P_{fert}). In the absence of any concomitant feed conversion improvements, a higher grain percentage in livestock feed would have a modest mitigation potential for agricultural area (-3.4%; -0.18 billion ha), with pasture reduction (-0.32 billion ha) offsetting the necessary increase in cropland (+0.14 billion ha). A similar effect is observed for GHG emissions (-1.5%; -0.18 $GtCO_2eq$), where negative emissions from pasture abandonment would offset any increases from cropland expansion and additional fertilization (Fig. S4). However, this would entail substantial increases in water withdrawals (+11.8%; +460 km^3) and nutrient flows (+9.4% N_{fert}, +8.4% P_{fert} ; +12.4 Tg N_{fert}, +1.92 Tg P_{fert}) from additional inputs. (Fig. 3; Fig. S4).

Only a few intervention combinations achieve risk reduction below safe thresholds

While interventions such as reducing animal calories, improved feed conversion ratios, and N&P management show considerable mitigation potential (Fig. 3), no single intervention is sufficient to stay below both critical risk thresholds for all four environmental limits. Here, we mapped the performance of all modelled predictions against their risk mitigation and intervention ambition level to generate a complete set of 1,048,576 possible combinations (Table S14; Fig. S5). We then queried this combination set to identify combinations that met the critical risk thresholds of 0.50 (exceedance *about as unlikely as not*) and 0.33 risk (exceedance *unlikely*) individually for each environmental limit and then combined across all limits (Fig. 4; Fig. S6-S9).

While 80.3% of modelled combinations achieve the risk <0.33 threshold for global surface water flows, the safe operating space is considerably more restricted for agricultural area (11.5% of all modelled combinations), nutrient cycles (10.2%) and GHG emissions (0.8%), with slightly higher numbers of scenarios meeting the risk <0.50 threshold (Fig. 4a; Fig. S6-S9). Only 0.81% (n = 8,244) of all combinations achieve a risk <0.50 across all environmental limits, with an even smaller subset of 0.02% (n = 204) combinations achieving the risk <0.33 threshold (Fig. 4). This finding reflects the interplay of synergies, trade-offs, and dependencies arising from different interventions and ambition levels and their respective efficacy across different environmental limits.

Analysing the intervention combinations that meet risk thresholds across all environmental limits reveals the required ambition levels for each intervention (Fig. 4b). Despite notable differences between risk < 0.50 and risk < 0.33 thresholds, over 97%, 80% and 70% of all compliant combinations entail Very High ambition levels for animal calories, N & P management, and feed conversion ratios respectively (Fig. 4b). Crop yields, plant calories (reduced overconsumption), waste and emissions intensity are the next most influential intervention group, with ~50% of risk < 0.50 and more than 70% of risk < 0.33 compliant combinations requiring a Very High level of ambition (Fig. 4b). Population is slightly less critical, with ~40% of risk < 0.50 and ~60% of risk < 0.33 compliant combinations requiring a Very High level of ambition. In general, more than 59% of risk < 0.33 compliant combinations require Very High ambition across demand-side interventions, highlighting their across-the-board risk mitigation potential.

In the case of the two remaining supply-side interventions (feed composition and water-use efficiency), there is a much broader range of ambition levels that achieve risk thresholds (Fig. 4a). For feed composition, High to Very High ambition, indicative of livestock systems that require more grain, is required across 48% of risk < 0.50 and 55% of risk < 0.33 combinations. Trade-offs associated with feed intensification for nutrient cycles appear to be offset by the modest benefits to agricultural area and GHG emissions (Fig. 3). Despite its specific mitigation potential for surface water flows specifically (Fig. 3; Fig. S8), water-use efficiency does not appear to play a role in the selection of overall low risk combinations, reflecting the sufficient risk mitigation potential from more universally effective interventions (e.g. demand-side interventions) and the generally safer status of the global surface water flow limit.

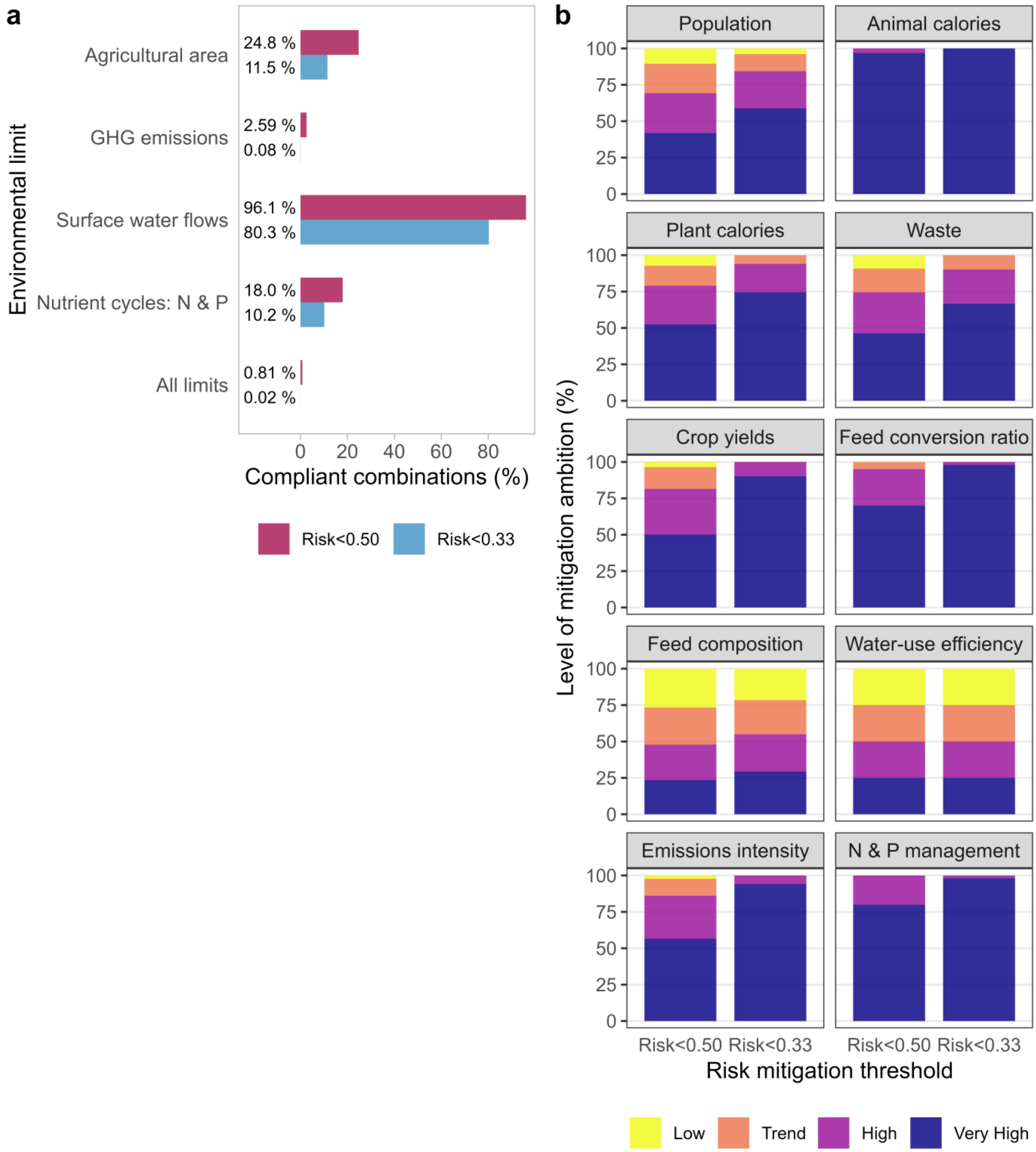

Fig. 4. Percentages of risk-compliant combinations and required intervention ambition levels to meet alternative risk thresholds. **a.** The horizontal bar plot displays the percentage out of a total of 1,048,576 possible combinations that meet each of the two risk thresholds (risk < 0.50 and risk < 0.33) for each environmental limit and combined for all limits. **b.** The vertical bar plots display the percentages of each of the four levels (Low, Trend, High, Very High) of mitigation ambition for the intervention combinations that meet each of the two risk thresholds for all environmental limits. See Note S7 for extended results and Data S4 for source data.

Diverse actions can enable risk-compliant intervention combinations

The option space of intervention combinations that would enable the food system to stay within all environmental limits is narrow (Fig. 4). Despite the significant feasibility challenges, highly ambitious mitigation levels remain within reach – provided the numerous and diverse opportunities for action across the food system are fully and promptly exploited. Based on the qualitative synthesis of the 64 systematically selected studies, we identified key on-ground actions at different stages of the food supply chain that could enable the level of mitigation ambition required across demand- and supply-side interventions (Table 3, Data S3).

Table 3. Mitigation actions discussed in reviewed studies mapped to relevant interventions. The table provides a non-exhaustive list of 58 actions with examples across the food system, as qualitatively mentioned in the 64 systematically selected studies. 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. Scope coverage follows supply-chain stages (i.e., farm-level, processing and retail, consumers, agricultural policy, research and development) previously defined in [62]. Actions are listed alphabetically within each scope category. For further detail and tallying of actions against solutions see Data S3.

		Interventions									
		Demand-side			Supply-side						
Scope	Action categories (examples)	Population	Diet	Waste (inc. loss)	Crop yields	Feed conversion	Feed composition	GHG intensity	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)			■							
Consumers	Dietary guidelines for healthy and sustainable diets		■	■							
	Education and awareness campaigns		■	■							
	Family planning (e.g., education and empowerment)	■	■								
	Food labeling regulations with sustainability scoring		■	■							
	Integrating sustainability in social protection programmes		■	■							
	Market-based instruments (e.g., carbon price, health tax)		■	■	■	■	■	■	■	■	■
	Novel protein sources (e.g., algae, mycoprotein, insects)		■								
	Nudges towards plant-based diets (e.g., reward schemes)		■	■							
	Nutrition counselling in maternal/childcare programmes		■								

Scope	Action categories (examples)	Population	Diet	Waste (inc. loss)	Crop yields	Feed conversion	Feed composition	GHG intensity	Water-use efficiency	Nutrient-use efficiency	Nutrient recycling
		Interventions									
	Scope / Action categories (examples)	**Demand-side**			**Supply-side**						
	Promotion of more sustainable diets in gastronomy		■	■							
	Public procurement (e.g., meals in schools and hospitality)		■	■							
	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 basin limits on extraction/application								■	■	■
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		■	■	■	■	■	■	■	■	■

Opportunities and challenges for achieving the required demand-side intervention levels

A major challenge to achieving the required levels of demand-side mitigation is the feasibility of implementing transformative global-scale actions within the available timeframe [13,52]. The required levels of mitigation by 2050 across diets, waste, and population are at odds with current patterns in high-income countries [63], the continued growth of the global middle class with associated increases in animal-source food (ASF) consumption [26,40], and trends in food waste [64,65] and population growth [40,66]. However, increasing social awareness of the environmental mitigation potential of demand-side actions and their co-benefits with health and well-being [31,38,39], coupled with emerging options [13] to overcome systemic financial and political challenges [52], 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 unlock technological innovation and the changes in choice infrastructure necessary for shifting consumer behavior.

The adoption of low animal-source food diets with significantly less ruminant meat [49] is critical. The pace of the nutrition transition[63] shows that equally rapid shifts towards ASF diets could be realizable with the right policy settings and retail environments[67]. This includes consumer-centered actions such as incorporating sustainability into dietary guidelines and food labels, education campaigns on sustainable diets, investment in healthier food environments, and pricing that reflects negative environmental and health externalities (Table 3). Promoting legumes, nuts, and seeds in high-income countries can reduce environmental risk while improving health outcomes [49]. Novel protein alternatives (e.g., plant-based or lab-grown substitutes, mycoprotein, and insects) could catalyze dietary shifts away from animal protein with potential environmental and health co-benefits [68,69], but their micronutrient content and broader social and economic implications warrant further consideration[70-72]. More equitable income distribution could facilitate dietary transitions [39]. Actions tailored to specific country contexts, underpinned by global monitoring efforts such as the Food Systems Countdown Initiative[73], could target behavioral feasibility challenges such as established social norms favoring meat consumption [74]. Models with an endogenous social acceptability component that dynamically account for changes in diets in response to changing social norms suggest that the low ASF diet is achievable by 2050 [75,76].

Similar actions could support a reduction in overconsumption and food waste, and therefore in plant calories, especially in upper- and middle-income countries where excess energy intake contributes to overweight and obesity [52,63]. Changes in sociocultural norms towards heathier diets can reduce excess plant calories (particularly from processed carbohydrates and vegetable oils) and food waste [63,77]. Effective interventions for reducing food waste include reductions in the size and type of servings in hospitality settings, changing nutritional guidelines in schools, and information campaigns [78]. These need to be accompanied by complementary action in the food retail environment such as improvements in food packaging and inventory management (Table 3). 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 encouraging progress already underway in this respect [65,79].

The significance of slowing population growth is often downplayed in food system studies [40,66]. Actions that could limit global population to 9.1 billion in 2050 include education to change social norms around family planning, empowering women, and reducing gender and other inequalities [31,46]. Such measures could support sustainable diet transitions by addressing the combined negative effects of population growth and the nutrition transition [40,63]. 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 help achieve the necessary mitigation ambition across all demand-side interventions (Table 3).

Opportunities and challenges for 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 can accelerate innovation and knowledge transfer across different geographic regions (Table 3).

Key actions to address large feed efficiency gaps across different livestock production systems [51] include better animal breeding and husbandry, improving feed digestibility through improved feed composition and supplements, and optimizing grazing management (Table 3). The overall feed conversion efficiency of the food system is tied to dietary preferences. Protein from aquaculture and crops has a higher conversion efficiency compared to that from terrestrial livestock [68,80,81]. Other options such as novel feeds (e.g., microbial protein, insects)[82] and novel protein alternatives could further increase the overall input efficiency of the food system while providing healthy protein.

Certain actions to improve feed conversion ratios, such as shifting to grain-based livestock production, risk increasing the amount of food-competing feed (FCF). Livestock systems that implement feed circularity[83] through the use of low-opportunity-cost biomass such as crop by-products[84], food waste and pasture [83] can reduce FCF demand (Table 3), but can only provide a limited amount of animal protein due to their more extensive nature [85,86]. This implies a contingency with a low ASF diet [87]. Furthermore, low-FCF systems are challenging in some settings and for some livestock types[83], despite although high-yielding grazing systems are found in Australia and New Zealand [51]. Further actions to reduce FCF demand include focusing on dairy herds (that produce both milk and meat) over pure beef herds [22,62] and locating ruminant grazing in areas with higher pasture productivity (Table 3).

Improved feeding practices and supplements can also reduce methane emissions from enteric fermentation [88]. Additional actions such as improvements in housing systems, manure storage (e.g. anaerobic digestion to reduce emissions from manure) and improved nutrient and residue management to reduce emissions from cropland soils and rice paddies can further reduce non-CO_2 emissions from crops and livestock [14,36,52] (Table 3). A carbon price is an established market-based mechanism to incentivize these actions and to also reduce land clearing and promote CO_2 sequestration through trees and soil enhancement [36]. While the modelled carbon price of US$200 tCO_2eq^{-1} is higher than the US$100 tCO_2eq^{-1} currently considered cost-effective [14], it is still feasible by 2050 [36] and offers significant technical mitigation potential – especially in South America and Africa [36].

A crop yield increase of 60% by 2050 relative to 2010 is assumed in most risk < 0.33 scenarios. An expected 30% increase follows historical (1970-2010) trends for cereal crops [50], with an observed ~18% increase between 2010 and 2022 [89]. Additional yield increases are possible through further investment and technology transfer in improved management practices, advanced agronomic (e.g., precision farming) and genetic (e.g., higher-yielding and climate-resilient) technologies, and additional fertilization in areas with high yield gaps [49,52], (Table 3). However, climate change could compromise yield gains in some crop-growing regions [90,91]. The results indicate that the negative consequences of higher input requirements required to achieve yield increases in some locations can be offset by improvements in water-use efficiency (WUE) and N & P management (Table 3).

Increasing global WUE by 5-15% requires additional investments in crop production techniques and technologies to those that can increase crop yields, including soil-water conservation and improved water management (e.g., rainwater harvesting, higher yields from rainfed agriculture, and deficit irrigation) (Table 3). The assumed WUE gains remain feasible given the plethora of actions available in different geographic contexts [9,53]. However, translating gains in WUE to actual water savings relies on robust water accounting, stricter enforcement of caps to prevent water misuse and misallocation, and a better understanding of behavioral responses of irrigators to increases in WUE [54].

Attaining the required levels of N & P management requires enhanced nutrient management across the food system (Table 3). This includes actions to increase nutrient-use efficiency (NUE) such as better placement and timing of fertilizers, precision irrigation, integrated weed, pest, and disease management, enhanced manure storage and spreading methods, and enhanced recycling of animal manures [55]. Soil conservation practices (e.g., cover crops, tillage management, buffer strips) can further enhance NUE by minimizing erosion and runoff [57]. Shifts in diets can also affect the overall NUE of the food system, with intensive livestock production associated with a lower NUE due to the crop mix required to satisfy feed demand [55]. In terms of recycling, recovering phosphorus from wastewater is currently more established and efficient compared to nitrogen [92], with few technologies able to maximize both N and P recovery at once[93]. However, up to ~35% of inorganic N from chemical fertilizer could in theory be offset by recycling nutrients from food waste and wastewater in fields [10].

DISCUSSION

Low-risk food system pathways must target key interventions

We find that unlikely exceedance (<0.33 risk) across all environmental limits in 2050 is contingent on the highest level of mitigation ambition for key interventions, namely animal calories, N & P management, feed conversion ratios and GHG emissions intensity. Strong efforts are also required to increase crop yields and to limit plant calories, food waste and population growth. Low-risk intervention combinations are also reflective of the significant challenge of reducing risk to below 0.33 for the GHG emissions and nutrient cycle limits, with both already in a high-risk state [4,5,31].

Our synthesis strongly supports a growing body of high-profile studies [7,8,12,25,26,49] that highlight diets low in animal-source foods as a key prerequisite for the food system to remain within environmental limits. This contradicts recent FAO reports[24,94] which downplay the role of diet change without explicit quantification of the environmental benefits of alternative interventions[23]. More broadly, our findings underline the central role of demand-side interventions. A key challenge that follows is how to turn around the slow progress to date in necessary actions (Table 3). Many interventions, including dietary change and waste reduction, are usually modelled as exogenous drivers, without adequate consideration of local biophysical constraints, affordability and sociocultural norms – all of which must be overcome to reach a societal tipping point that enables large-scale transitions in food consumption [16,95-97].

The urgency of critical supply-side interventions such as reducing GHG intensity and improving nutrient management through technological innovation and agricultural practices is well-established [14,98] . So too is the importance of increasing crop yields, as seen in consistent investment and gains in recent decades[15,89], despite persistently high yield gaps in some regions. Our findings also emphasize the critical role of feed efficiency. Beyond its significant methane reduction potential [51,88,99,100], most studies did not explicitly consider feed efficiency interventions or their interactions with feed composition and alternative diets (Table S8), although several authors acknowledge its importance (Table 3). Our findings are at odds with the 'Dublin Declaration' which advocates for maintaining or increasing livestock numbers through agroecology[101]. However, agroecological systems have lower feed efficiencies and must be paired with diets low in animal-source foods [87,102]. Since low-risk food system pathways require low animal-source food diets and high feed efficiencies, actions that enable shifts away from ruminants towards animal products with higher feed efficiencies (e.g., aquaculture, poultry and eggs), and promote more affordable and palatable plant-based and novel protein sources, are more effective for reducing environmental impacts. Additional actions may also be necessary to minimize any negative trade-offs for animal and human in intensive livestock systems[103].

Target setting and risk assessment of food systems

Explicit target-setting, such as the proposed 'net zero' equivalent target for the food system [104], can provide the impetus towards transformative actions. Equally ambitious targets are necessary for all environmental indicators [3,105,106], and broader Sustainable Development Goal indicators – especially those intrinsically linked to the food system such as food and nutrition security, animal and human welfare[103], and livelihoods [107,108]. While some mitigation actions are likely to show considerable co-benefits, others, especially those that require high R&D investment, could entail significant costs to producers and consumers, with potentially adverse impacts on food security [14,52]. While our risk assessment focuses on system-level risk metrics, sub-indicator results show that certain interventions can have disparate effects (e.g., between cropland and pasture, or between different greenhouse gases) that may also warrant shorter-term targets. For example, the 45% methane reduction target by 2030 recommended in UNEP's Global Methane Assessment [109] reflects methane's role as a short-lived but potent climate pollutant. Similar interim targets for other indicators can inform appropriate 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 to identify optimal intervention portfolios to meet these targets.

Interactions across Earth system processes are complex and amplifying, and safeguarding all environmental limits is therefore essential [1,2,6,31]. The presence of significant regional risk thresholds as is the case for nutrient cycles [98], and water [5,9,110], highlights the importance of setting environmental limits and targets at different levels, from global to sub-national (e.g., at basin level). Our risk estimates do not encompass all environmental limits and their potential interactions [4,33,111], and do not explicitly account for regional or seasonal exceedances [9,92]. Interventions such as water-use efficiency are likely to be extremely important in the context of local environmental limits, despite the relatively low level of global risk[5]. Additional interventions that achieve spatially optimized outcomes [112,113] may also be required to ensure adherence to both global and local environmental limits.

Our risk assessment framework does not explicitly consider or quantify feasibility challenges [13,74]. Many studies focus on a limited combination of highly ambitious best-case interventions, raising concerns around feasibility [74,114,115]. While our approach does include more comprehensive suites of interventions, food system models must better incorporate feasibility evaluation [16,74,116] to allow more realistic comparisons of different ambition levels across multiple interventions based on technological, economic, socio-cultural, and institutional barriers to identify optimum action pathways. Furthermore, while our risk estimates capture the spread across underlying models, our approach does not capture how specific actions could influence the environmental performance of a given intervention. For example, crop yields could increase because of total factor productivity [46], but could also increase through additional irrigation and fertilization inputs. Different actions and mechanisms of implementation have diverse synergies or trade-offs across environmental indicators and may also entail divergent implementation challenges [13,97].

Towards improved syntheses of food system interventions

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. Studies underline the importance of the timing and pace of implementation [7,25], especially for climate change where the remaining carbon budget also depends on decarbonization trajectories in other key sectors such as energy and transport [12,36]. Dynamic process-based models consider non-linearities and saturation effects in intervention effectiveness associated with trends in technology and consumer behavior [39,75,81], as well regional heterogeneity in key food demand drivers (e.g., population, income and agricultural R&D) and their interactions with food prices [117]. Future syntheses could compare non-linearities in implementation using timeseries multi-model ensembles based on diverse scenario narratives. Improved data sharing and harmonization of scenarios and intervention parameters, in a similar fashion to IPCC climate mitigation scenarios [36,41], would greatly facilitate future syntheses. Recent progress along these lines includes a new generation of multi-model target-seeking scenarios that incorporate diverse and coherent sustainability perspectives such as the sustainable development pathways [106].

Our work provides the most comprehensive synthesis and risk assessment to date on the mitigation potential of possible 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 environmental limits. While we consider many possible futures, there are potentially many 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, given the considerable risk mitigation potential of diet shifts and their inherent feasibility challenges [15,25,26], the emergence of novel protein alternatives [69] or other future technologies [13] could expand the option space by accelerating sustainable dietary transitions, with food system models only just starting to explicitly incorporate some of these dynamics between technology and diet change [22,72,81]. Future research needs to comprehensively synthesise the risk mitigation potential of available interventions and the numerous actions available to enable them across different contexts.

METHODS

Systematic review and input dataset compilation

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 [118,119]. We developed a universal search string refined using an article test list of 20 highly cited articles. We then used this search string to search across four major academic databases (ProQuest, Scopus, Web of Science, Science Direct) to identify peer-reviewed journal articles and book chapters that contained quantitative scenario projections of global environmental impacts explicitly associated with food production for the year 2050 (Note S1; Fig. S1). We complemented our academic literature search with a comprehensive search of the grey literature, focusing on key reports from major food-related organizations (FAO, World Bank, CGIAR, IFPRI, WRI, UNEP, UNCCD) using the Google search engine. The initial search was carried out in November 2017, with periodic updates through search engine alerts (ProQuest, Scopus, Web of Science and Google Scholar) up to and including November 2024. We also ran an updated systematic search with a slightly modified search string in early December 2024 to ensure that any literature published since the initial search had been captured (Table S1). For details of all search strings, exclusion criteria, and all search results and study screening see Note S1 and Data S2.

A total of 1688 titles and abstracts were screened and, following reference scanning ('snowballing') and search alerts and co-author suggestions, 191 full texts were assessed for inclusion. From these, 64 studies met all inclusion criteria for qualitative synthesis and were also shortlisted for quantitative synthesis (Note S1; Fig. S1). Following data extraction from each publication (including supplementary material or code), and data directly obtained from the lead authors of each study, we developed a comprehensive input database (Data S1) of published global food system model scenarios with impact estimates and interventions for eight commonly used environmental indicators related to four key environmental limits (Note S2). Following strict exclusion criteria (Table S5), we created a harmonized dataset from 26 studies with recent and consistent base year values and variable specification representing 2,246 future scenario projections and 946 scenario narratives, and assembled a full dataset of input parameters that contained the minimum set of 29 quantitative variables necessary to parameterize all interventions (Note S3, Table S4). The resulting dataset was used to train the meta-regression models (see below). This follows [120] who only used a selection of studies that could be harmonized. Study authors who contributed significantly to the data compilation and harmonization effort were invited to become co-authors.

Defining food system specific environmental limits

We defined food system specific environmental limits for four earth system processes for the year 2050 based on the latest scientific consensus on global environmental limits and other literature (Table 1; Note S2). We selected eight environmental indicators and specified environmental limits based on available model outputs in the literature, as well as on current scientific consensus around environmental limits [4,5]. Uncertainty in environmental limits was incorporated by specifying triangular probability density functions (PDFs), commonly used in risk analysis [121], characterized by best estimate, minimum, and maximum values. 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 GHG emissions, we used data from the AR6 Scenarios Database v1.1 [41], 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 (Table S2) .[36]

Environmental limits for the food system account for possible trajectories in relevant non-food sectors which also exert a significant pressure on each of the limits (Table 1; Note S2). The PDF representing the environmental limit for GHG emissions drawn from the AR6 Scenarios Database already encompassed assumptions around the decarbonization trajectories in other key sectors such as energy and transport. Nutrient cycle limits for N and P fertilizer were already specific to agriculture.[4,5,8] For the agricultural area limit we considered the range in possible deforestation trajectories for reasons other than agricultural expansion[122,123], while for the surface water flows limit, we considered the range in non-agricultural water demand (i.e., from households and industry) as well as the relative contributions of surface water and groundwater [42]. (Table 1; Table S2). Our environmental limit PDFs therefore encompassed both the inherent uncertainty in defining the Earth system's safe operating space, as well as the range of possible trajectories of relevant non-food sectors and share of each environmental limit available to the food system in 2050 (Note S2).

Meta-regression modeling and intervention effect size

Following data extraction, study selection and extensive harmonization of data inputs (Note S3), we used the curated dataset of scenario projections assembled from the 26 selected studies (Table S3; Data S1) to fit linear mixed-effects meta-regression models[120,124] for each environmental indicator. We then used the fitted statistical models to generate a comprehensive database of predictions for 2050. We tested both a random slope and 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 [120,124]. We fitted eight linear mixed-effects models (LMMs), one for each environmental indicator using a restricted maximum-likelihood routine implemented in the R package *lme4* [125].

We used the log response ratio of environmental impact computed as *ln (future estimate/base year estimate)* as the response variable. An exception was made for pasture, where we used % change as the response variable [120]), and CO_2 LUC (see below). The independent variables representing relevant demand- and supply-side interventions for each environmental indicator were parameterized as composite variables and fixed-effect regressors to emulate biophysical processes in the original models (Note S6). 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 [41]. We instead trained an LMM using 2203 vetted 2010-2050 observations in the AR6 Scenarios Database [41], 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 and pasture as independent variables (Note S4; Note S5).

We carried out model selection and validated prediction accuracy through cross-validation, following best practice for predictive models [126]. 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* [127] which explicitly controls for the random effect structure in LMMs. We formulated and tested alternative model structures based on a process-based logic that replicates model structures of selected studies using aggregates of independent predictors, e.g., total feed demand for ruminant meat (Note S4; Note S5). We selected models based on the *root mean square* metric 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 [18] which improved the fit for the cropland, water withdrawals, 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* [128] and *LMERConvenienceFunctions* [129] packages (see Note S4). The final selection of models was guided by marginal (i.e., variance explained by fixed effects) and conditional (i.e., variance explained by fixed and random effects) R^2 estimates calculated using the R package *MuMIn* [130] following the method of [131]. Selected models had cross-validated marginal and conditional R^2 values above 0.64 and 0.79 respectively, reflecting the high percentage of overall variance explained by all LMMs (Table S14).

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* [132] 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 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 S24) to derive estimates in absolute units for 2050. To compute effect sizes for different interventions levels, we calculated intervention-level averages by summarizing (mean and standard deviation) mitigation potential for each intervention level across each indicator (Fig. 3; Fig. S4) based on a one-at-a-time sensitivity approach [20].

Risk assessment and analysis of risk-compliant intervention combinations

Mean predictions of the impact of interventions across each of the eight 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. 1; Note S4). 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 (agricultural area, GHG emissions, surface water flows, and one each for the two nutrient cycle indicators, N_{fert} and P_{fert}).

To identify intervention combinations that met IPCC-calibrated uncertainty risk thresholds [61], we mapped the performance of all intervention combinations against their risk mitigation and ambition level. We did this individually, for each of the four environmental limits, and combined across all limits, yielding a total of 1,048,576 intervention level combinations across environmental limits. 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 [60,61]. 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 to below each of the two risk thresholds.

Limitations

Our modelled intervention levels (Low, Trend, High, Very High) are representative of the range of ambition within the selected studies but do not account for the potentially diverse feasibility challenges (e.g., technological or behavioral) across different types of interventions. As a result, the feasibility of different levels of ambition is not comparable across interventions (e.g., Very High ambition for diets vis-à-vis N & P management). The costing of alternative interventions and their applicability across different geographic regions and socioeconomic contexts is an important topic of further investigation [16,133]. Further research could extend our work to calculate effect sizes of a more diverse range of available on- and off-farm mitigation actions that relate to each of the interventions modelled here.

The four environmental limits and the eight environmental indicators selected to represent them were chosen due to their abundance and consistent use in the food system modeling literature, ensuring adequate sample sizes for statistical analysis. This meant that some indicators that are better proxies of risk for specific environmental limits, such as, for example, nutrient surplus indicators [5,98], could not be used in our analysis. Similarly, the food system is a major driver of impact across several other environmental limits that were not considered here (Note S6), most notably exerting a significant impact on biosphere integrity [15]. While our estimates of environmental limits encompassed the wide uncertainty ranges incorporated in published estimates and a range in potential future shares of the global food system (Note S2), studies highlight the added importance of spatially explicit assessments that account for both local and global impacts [5,9,98]. Beyond environmental limits, a sustainable food system must also adhere to Earth system justice principles [5,31]. While our diet combinations were compliant with food and nutrition security requirements (Note S4), our analysis could be extended to other aspects of health and Earth system justice.

The global scope and statistical nature of our analysis did not allow us to encompass all possible interventions and their interactions. While the LMMs are formulated with a process-based logic similar to that of the underlying models that enables interactions between interventions (e.g., changes in diets occurring concurrently with changes in feed efficiency or feed composition), they do not encompass all processes modelled in the original models, and are therefore not intended to fully emulate their individual responses (Note S5). For example, we do not consider parameters such as pasture productivity [134], distinction between rainfed and irrigated yields, explicit modelling of land-use regulation and conservation actions [20], or the potential for non-linear responses to efficiency parameters such as WUE or NUE or declining spatial efficiency across regions [135,136] (Note S6). We also do not account for interactions between intervention levels environmental limits, for example where rapid dietary transitions alter the remaining carbon budget due to their significant methane abatement [25].

RESOURCE AVAILABILITY

Lead contact

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Materials availability

This study generated no new materials.

Data and code 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.14523155. Extended results are available at: https://doi.org/10.5281/zenodo.14523376.

ACKNOWLEDGEMENTS

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 for helpful correspondence related to data quality. The work was supported by Deakin University.

SUPPLEMENTAL INFORMATION

Document S1. Supplemental methods and results, Notes S1-S7, Figures S1-S9, Tables S1-S24
Data S1. Input database (.xlsx)
Data S2. Systematic search details (.xlsx)
Data S3. Action-intervention mapping (.xlsx)
Data S4. Source data for figures (.xlsx)

REFERENCES

1. Rockström, J., Steffen, W., Noone, K., Persson, A., Chapin, F.S., Lambin, E.F., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J., et al. (2009). A safe operating space for humanity. Nature *461*, 472-475.
2. Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., de Vries, W., de Wit, C.A., et al. (2015). Planetary boundaries: Guiding human development on a changing planet. Science *347*. 10.1126/science.1259855.
3. Rockström, J., Edenhofer, O., Gaertner, J., and DeClerck, F. (2020). Planet-proofing the global food system. Nat. Food *1*, 3-5. 10.1038/s43016-019-0010-4.
4. Richardson, K., Steffen, W., Lucht, W., Bendtsen, J., Cornell, S.E., Donges, J.F., Drüke, M., Fetzer, I., Bala, G., von Bloh, W., et al. (2023). Earth beyond six of nine planetary boundaries. Sci. Adv. *9*, eadh2458. doi:10.1126/sciadv.adh2458.
5. Rockström, J., Gupta, J., Qin, D., Lade, S.J., Abrams, J.F., Andersen, L.S., Armstrong McKay, D.I., Bai, X., Bala, G., Bunn, S.E., et al. (2023). Safe and just Earth system boundaries. Nature *619*, 102-111. 10.1038/s41586-023-06083-8.
6. Rockström, J., Kotzé, L., Milutinović, S., Biermann, F., Brovkin, V., Donges, J., Ebbesson, J., French, D., Gupta, J., Kim, R., et al. (2024). The planetary commons: A new paradigm for safeguarding Earth-regulating systems in the Anthropocene. Proc. Natl. Acad. Sci. U.S.A. *121*, e2301531121. doi:10.1073/pnas.2301531121.
7. Clark, M.A., Domingo, N.G.G., Colgan, K., Thakrar, S.K., Tilman, D., Lynch, J., Azevedo, I.L., and Hill, J.D. (2020). Global food system emissions could preclude achieving the 1.5° and 2°C climate change targets. Science *370*, 705-708. 10.1126/science.aba7357.
8. Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B.L., Lassaletta, L., de Vries, W., Vermeulen, S.J., Herrero, M., Carlson, K.M., et al. (2018). Options for keeping the food system within environmental limits. Nature *562*, 519-525. 10.1038/s41586-018-0594-0.
9. Gerten, D., Heck, V., Jägermeyr, J., Bodirsky, B.L., Fetzer, I., Jalava, M., Kummu, M., Lucht, W., Rockström, J., Schaphoff, S., and Schellnhuber, H.J. (2020). Feeding ten billion people is possible within four terrestrial planetary boundaries. Nat. Sustain. 10.1038/s41893-019-0465-1.
10. Conijn, J.G., Bindraban, P.S., Schröder, J.J., and Jongschaap, R.E.E. (2018). Can our global food system meet food demand within planetary boundaries? Agric. Ecosyst. Environ. *251*, 244-256. https://doi.org/10.1016/j.agee.2017.06.001.
11. Bowles, N., Alexander, S., and Hadjikakou, M. (2019). The livestock sector and planetary boundaries: A 'limits to growth' perspective with dietary implications. Ecol. Econ. *160*, 128-136. https://doi.org/10.1016/j.ecolecon.2019.01.033.
12. Ivanovich, C.C., Sun, T., Gordon, D.R., and Ocko, I.B. (2023). Future warming from global food consumption. Nat. Clim. Chang. *13*, 297-302. 10.1038/s41558-023-01605-8.
13. Herrero, M., Thornton, P.K., Mason-D'Croz, D., Palmer, J., Benton, T.G., Bodirsky, B.L., Bogard, J.R., Hall, A., Lee, B., Nyborg, K., et al. (2020). Innovation can accelerate the transition towards a sustainable food system. Nat. Food *1*, 266-272. 10.1038/s43016-020-0074-1.
14. Roe, S., Streck, C., Beach, R., Busch, J., Chapman, M., Daioglou, V., Deppermann, A., Doelman, J., Emmet-Booth, J., Engelmann, J., et al. (2021). Land-based measures to mitigate climate change: Potential and feasibility by country. Glob. Chang. Biol. *27*, 6025-6058.
15. Erb, K.-H., Matej, S., Haberl, H., and Gingrich, S. (2024). Sustainable land systems in the Anthropocene: Navigating the global land squeeze. One Earth *7*, 1170-1186. 10.1016/j.oneear.2024.06.011.
16. Moallemi, E.A., Hall, A., Leith, P., Miller, M., Sperling, F., Raven, R., Frantzeskaki, N., Palmer, J., Battaglia, M., Bruce, J., et al. (2024). Shortcuts for accelerating food system transitions. One Earth *7*, 365-369. 10.1016/j.oneear.2024.01.010.
17. Thornton, P., Mason D'Croz, D., Kugler, C., Remans, R., Zornetzer, H., and Herrero, M. (2024). Enabling food system innovation: accelerators for change. Glob. Food Sec. *40*, 100738. https://doi.org/10.1016/j.gfs.2023.100738.

18. Alexander, P., Prestele, R., Verburg, P.H., Arneth, A., Baranzelli, C., Batista e Silva, F., Brown, C., Butler, A., Calvin, K., Dendoncker, N., et al. (2017). Assessing uncertainties in land cover projections. Glob. Chang. Biol. *23*, 767-781. doi:10.1111/gcb.13447.

19. Reilly, M., and Willenbockel, D. (2010). Managing uncertainty: a review of food system scenario analysis and modelling. Philos. Trans. R. Soc. Lond., B, Biol. Sci. *365*, 3049-3063. 10.1098/rstb.2010.0141.

20. Stehfest, E., van Zeist, W.-J., Valin, H., Havlik, P., Popp, A., Kyle, P., Tabeau, A., Mason-D'Croz, D., Hasegawa, T., Bodirsky, B.L., et al. (2019). Key determinants of global land-use projections. Nat. Commun. *10*, 2166. 10.1038/s41467-019-09945-w.

21. Béné, C., Oosterveer, P., Lamotte, L., Brouwer, I.D., de Haan, S., Prager, S.D., Talsma, E.F., and Khoury, C.K. (2019). When food systems meet sustainability – Current narratives and implications for actions. World Development *113*, 116-130. https://doi.org/10.1016/j.worlddev.2018.08.011.

22. Röös, E., Bajželj, B., Smith, P., Patel, M., Little, D., and Garnett, T. (2017). Greedy or needy? Land use and climate impacts of food in 2050 under different livestock futures. Glob. Environ. Chang. *47*, 1-12. https://doi.org/10.1016/j.gloenvcha.2017.09.001.

23. Verkuijl, C., Dutkiewicz, J., Scherer, L., Behrens, P., Lazarus, M., Hötzel, M.J., Nordquist, R., and Hayek, M. (2024). FAO's 1.5 °C roadmap for food systems falls short. Nat. Food. 10.1038/s43016-024-00950-x.

24. FAO (2023). Pathways towards lower emissions – A global assessment of the greenhouse gas emissions and mitigation options from livestock agrifood systems. Food and Agriculture Organization of the United Nations.

25. Humpenöder, F., Popp, A., Merfort, L., Luderer, G., Weindl, I., Bodirsky, B.L., Stevanović, M., Klein, D., Rodrigues, R., Bauer, N., et al. (2024). Food matters: Dietary shifts increase the feasibility of 1.5°C pathways in line with the Paris Agreement. Sci. Adv. *10*, eadj3832. doi:10.1126/sciadv.adj3832.

26. Li, Y., He, P., Shan, Y., Li, Y., Hang, Y., Shao, S., Ruzzenenti, F., and Hubacek, K. (2024). Reducing climate change impacts from the global food system through diet shifts. Nat. Clim. Chang. 10.1038/s41558-024-02084-1.

27. Schmitz, C., van Meijl, H., Kyle, P., Nelson, G.C., Fujimori, S., Gurgel, A., Havlik, P., Heyhoe, E., d'Croz, D.M., Popp, A., et al. (2014). Land-use change trajectories up to 2050: insights from a global agro-economic model comparison. Agric. Econ. *45*, 69-84. 10.1111/agec.12090.

28. Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B.L., Dietrich, J.P., Doelmann, J.C., Gusti, M., et al. (2017). Land-use futures in the shared socio-economic pathways. Glob. Environ. Chang. *42*, 331-345. https://doi.org/10.1016/j.gloenvcha.2016.10.002.

29. Clark, M., Hill, J., and Tilman, D. (2018). The Diet, Health, and Environment Trilemma. Annu. Rev. Environ. Resour. *43*, 109-134. 10.1146/annurev-environ-102017-025957.

30. Valin, H., Hertel, T., Bodirsky, B.L., Hasegawa, T., and Stehfest, E. (2021). Achieving Zero Hunger by 2030 A Review of Quantitative Assessments of Synergies and Tradeoffs amongst the UN Sustainable Development Goals. The Scientific Group of the UN Food Systems Summit 26 May 2021. Bonn: Center for Development Research (ZEF) in cooperation with the Scientific Group for the UN Food System Summit 2021.

31. Gupta, J., Bai, X., Liverman, D.M., Rockström, J., Qin, D., Stewart-Koster, B., Rocha, J.C., Jacobson, L., Abrams, J.F., Andersen, L.S., et al. (2024). A just world on a safe planet: a Lancet Planetary Health–Earth Commission report on Earth-system boundaries, translations, and transformations. Lancet Planet. Health *8*, e813-e873. 10.1016/S2542-5196(24)00042-1.

32. Baum, S.D., and Handoh, I.C. (2014). Integrating the planetary boundaries and global catastrophic risk paradigms. Ecol. Econ. *107*, 13-21. https://doi.org/10.1016/j.ecolecon.2014.07.024.

33. Lade, S.J., Steffen, W., de Vries, W., Carpenter, S.R., Donges, J.F., Gerten, D., Hoff, H., Newbold, T., Richardson, K., and Rockström, J. (2019). Human impacts on planetary boundaries amplified by Earth system interactions. Nat. Sustain. *3*, 119-128. 10.1038/s41893-019-0454-4.

34. van Vuuren, D.P., Kok, M.T.J., Girod, B., Lucas, P.L., and de Vries, B. (2012). Scenarios in Global Environmental Assessments: Key characteristics and lessons for future use. Glob. Environ. Chang. *22*, 884-895. https://doi.org/10.1016/j.gloenvcha.2012.06.001.

35. Roe, S., Streck, C., Obersteiner, M., Frank, S., Griscom, B., Drouet, L., Fricko, O., Gusti, M., Harris, N., Hasegawa, T., et al. (2019). Contribution of the land sector to a 1.5 °C world. Nat. Clim. Chang. 10.1038/s41558-019-0591-9.

36. Nabuurs, G.-J., R. Mrabet, A. Abu Hatab, M. Bustamante, H. Clark, P. Havlík, J. House, C. Mbow, K.N. Ninan, A. Popp, S. Roe, B. Sohngen, S. Towprayoon (2022). Agriculture, Forestry and Other Land Uses (AFOLU). In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, ed. (Cambridge University Press).

37. Bajzelj, B., Richards, K.S., Allwood, J.M., Smith, P., Dennis, J.S., Curmi, E., and Gilligan, C.A. (2014). Importance of food-demand management for climate mitigation. Nat. Clim. Chang. *4*, 924-929. http://dx.doi.org/10.1038/nclimate2353.

38. Creutzig, F., Niamir, L., Bai, X., Callaghan, M., Cullen, J., Díaz-José, J., Figueroa, M., Grubler, A., Lamb, W.F., Leip, A., et al. (2022). Demand-side solutions to climate change mitigation consistent with high levels of well-being. Nat. Clim. Chang. *12*, 36-46. 10.1038/s41558-021-01219-y.

39. Bodirsky, B.L., Chen, D.M.-C., Weindl, I., Soergel, B., Beier, F., Molina Bacca, E.J., Gaupp, F., Popp, A., and Lotze-Campen, H. (2022). Integrating degrowth and efficiency perspectives enables an emission-neutral food system by 2100. Nat. Food. 10.1038/s43016-022-00500-3.

40. Crist, E., Mora, C., and Engelman, R. (2017). The interaction of human population, food production, and biodiversity protection. Science *356*, 260-264. 10.1126/science.aal2011.

41. Byers, E., Krey, V., Kriegler, E., Riahi, K., Schaeffer, R., Kikstra, J., Lamboll, R., Nicholls, Z., Sanstad, M., Smith, C., et al. (2022). AR6 Scenarios Database hosted by IIASA. International Institute for Applied Systems Analysis.

42. Niazi, H., Wild, T.B., Turner, S.W.D., Graham, N.T., Hejazi, M., Msangi, S., Kim, S., Lamontagne, J.R., and Zhao, M. (2024). Global peak water limit of future groundwater withdrawals. Nat. Sustain. *7*, 413-422. 10.1038/s41893-024-01306-w.

43. Richter, B.D., Davis, M.M., Apse, C., and Konrad, C. (2011). A Presumptive Standard for Environmental Flow Protection. River Research and Applications *28*, 1312-1321. 10.1002/rra.1511.

44. UN DESA (2024). World Population Prospects 2024: Summary of Results (UN DESA/POP/2024/TR/NO. 9). United Nations Department of Economic and Social Affairs, Population Division.

45. WIC, I. (2024). Population and Human Capital Projections - 2023. IIASA and Wittgenstein Center (WIC).

46. Searchinger, T., Waite, R., Hanson, C., Ranganathan, J., Dumas, P., and Matthews, E. (2018). Creating a Sustainable Food Future: A Menu of Solutions to Feed Nearly 10 Billion People by 2050. World Resources Institute. https://www.wri.org/publication/creating-sustainable-food-future.

47. WHO. (2004). Vitamin and mineral requirements in human nutrition, Second Edition (World Health Organization and Food and Agriculture Organization of the United Nations).

48. Hiç, C., Pradhan, P., Rybski, D., and Kropp, J.P. (2016). Food Surplus and Its Climate Burdens. Environ. Sci. Techno. *50*, 4269-4277. 10.1021/acs.est.5b05088.

49. Willett, W., Rockström, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., Garnett, T., Tilman, D., DeClerck, F., Wood, A., et al. (2019). Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. The Lancet *393*, 447-492. 10.1016/S0140-6736(18)31788-4.

50. van Zeist, W.-J., Stehfest, E., Doelman, J.C., Valin, H., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Humpenöder, F., Kyle, P., et al. (2020). Are scenario projections overly optimistic about future yield progress? Glob. Environ. Chang. *64*, 102120. https://doi.org/10.1016/j.gloenvcha.2020.102120.

51. Herrero, M., Havlík, P., Valin, H., Notenbaert, A., Rufino, M.C., Thornton, P.K., Blümmel, M., Weiss, F., Grace, D., and Obersteiner, M. (2013). Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. Proc. Natl. Acad. Sci. U.S.A. *110*, 20888-20893. 10.1073/pnas.1308149110.

52. Zurek, M., Hebinck, A., and Selomane, O. (2022). Climate change and the urgency to transform food systems. Science *376*, 1416-1421. doi:10.1126/science.abo2364.

53. de Fraiture, C., and Wichelns, D. (2010). Satisfying future water demands for agriculture. Agric. Water Manage. *97*, 502-511. https://doi.org/10.1016/j.agwat.2009.08.008.

54. Grafton, R.Q., Williams, J., Perry, C.J., Molle, F., Ringler, C., Steduto, P., Udall, B., Wheeler, S.A., Wang, Y., Garrick, D., and Allen, R.G. (2018). The paradox of irrigation efficiency. Science *361*, 748-750. 10.1126/science.aat9314.

55. Sutton, M.A., Bleeker, A., Howard, C., Bekunda, M., Grizzetti, B., De Vries, W., Van Grinsven, H., Abrol, Y., Adhya, T., Billen, G., et al. (2013). Our Nutrient World: The challenge to produce more food and energy with less pollution (Global Overview of Nutrient Management. Centre for Ecology and Hydrology, Edinburgh on behalf of the Global Partnership on Nutrient Management and the International Nitrogen Initiative.).

56. Zhang, X., Zou, T., Lassaletta, L., Mueller, N.D., Tubiello, F.N., Lisk, M.D., Lu, C., Conant, R.T., Dorich, C.D., Gerber, J., et al. (2021). Quantification of global and national nitrogen budgets for crop production. Nat. Food *2*, 529-540. 10.1038/s43016-021-00318-5.

57. Beusen, A.H.W., Doelman, J.C., Van Beek, L.P.H., Van Puijenbroek, P.J.T.M., Mogollón, J.M., Van Grinsven, H.J.M., Stehfest, E., Van Vuuren, D.P., and Bouwman, A.F. (2022). Exploring river nitrogen and phosphorus loading and export to global coastal waters in the Shared Socio-economic pathways. Glob. Environ. Chang. *72*, 102426. https://doi.org/10.1016/j.gloenvcha.2021.102426.

58. Bodirsky, B.L., Popp, A., Lotze-Campen, H., Dietrich, J.P., Rolinski, S., Weindl, I., Schmitz, C., Müller, C., Bonsch, M., Humpenöder, F., et al. (2014). Reactive nitrogen requirements to feed the world in 2050 and potential to mitigate nitrogen pollution. Nat. Commun. *5*, 3858. 10.1038/ncomms4858.

59. Mastrandrea, M.D., and Schneider, S.H. (2004). Probabilistic Integrated Assessment of "Dangerous" Climate Change. Science *304*, 571-575. 10.1126/science.1094147.

60. Schleussner, C.-F., Ganti, G., Rogelj, J., and Gidden, M.J. (2022). An emission pathway classification reflecting the Paris Agreement climate objectives. Commun. Earth Environ. *3*, 135. 10.1038/s43247-022-00467-w.

61. Mastrandrea, M.D., C.B. Field, T.F. Stocker, O. Edenhofer, K.L. Ebi, D.J. Frame, H. Held, E. Kriegler, K.J. Mach,, and P.R. Matschoss, G.-K.P., G.W. Yohe, F.W. Zwiers (2010). Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties. Intergovernmental Panel on Climate Change (IPCC). Available at: https://www.ipcc.ch/site/assets/uploads/2018/05/uncertainty-guidance-note.pdf.

62. Poore, J., and Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. Science *360*, 987-992. 10.1126/science.aaq0216.

63. Bodirsky, B.L., Dietrich, J.P., Martinelli, E., Stenstad, A., Pradhan, P., Gabrysch, S., Mishra, A., Weindl, I., Le Mouël, C., Rolinski, S., et al. (2020). The ongoing nutrition transition thwarts long-term targets for food security, public health and environmental protection. Scientific Reports *10*, 19778. 10.1038/s41598-020-75213-3.

64. Lopez Barrera, E., and Hertel, T. (2021). Global food waste across the income spectrum: Implications for food prices, production and resource use. Food Policy *98*, 101874. https://doi.org/10.1016/j.foodpol.2020.101874.

65. UNEP (2021). Food Waste Index Report 2021. United Nations Environment Programme, . https://www.unep.org/resources/report/unep-food-waste-index-report-2021.

66. Ehrlich, P. (2021). Why no mention of overpopulation in talk of food systems? Nat. Food *598*, 257.

67. Vermeulen, S.J., Park, T., Khoury, C.K., and Béné, C. (2020). Changing diets and the transformation of the global food system. Ann. N. Y. Acad. Sci. *1478*, 3-17. https://doi.org/10.1111/nyas.14446.

68. Parodi, A., Leip, A., De Boer, I.J.M., Slegers, P.M., Ziegler, F., Temme, E.H.M., Herrero, M., Tuomisto, H., Valin, H., Van Middelaar, C.E., et al. (2018). The potential of future foods for sustainable and healthy diets. Nat. Sustain. *1*, 782-789. 10.1038/s41893-018-0189-7.

69. Lumsden, C.L., Jägermeyr, J., Ziska, L., and Fanzo, J. (2024). Critical overview of the implications of a global protein transition in the face of climate change: Key unknowns and research imperatives. One Earth *7*, 1187-1201. 10.1016/j.oneear.2024.06.013.

70. Bunge, A.C., Wood, A., Halloran, A., and Gordon, L.J. (2022). A systematic scoping review of the sustainability of vertical farming, plant-based alternatives, food delivery services and blockchain in food systems. Nat. Food. 10.1038/s43016-022-00622-8.

71. Tuomisto, H.L. (2019). Vertical Farming and Cultured Meat: Immature Technologies for Urgent Problems. One Earth *1*, 275-277. https://doi.org/10.1016/j.oneear.2019.10.024.

72. Mason-D'Croz, D., Barnhill, A., Bernstein, J., Bogard, J., Dennis, G., Dixon, P., Fanzo, J., Herrero, M., McLaren, R., Palmer, J., et al. (2022). Ethical and economic implications of the adoption of novel plant-based beef substitutes in the USA: a general equilibrium modelling study. Lancet Planet. Health *6*, e658-e669. 10.1016/S2542-5196(22)00169-3.

73. Schneider, K.R., Fanzo, J., Haddad, L., Herrero, M., Moncayo, J.R., Herforth, A., Remans, R., Guarin, A., Resnick, D., Covic, N., et al. (2023). The state of food systems worldwide in the countdown to 2030. Nat. Food *4*, 1090-1110. 10.1038/s43016-023-00885-9.

74. Nielsen, K.S., Stern, P.C., Dietz, T., Gilligan, J.M., van Vuuren, D.P., Figueroa, M.J., Folke, C., Gwozdz, W., Ivanova, D., Reisch, L.A., et al. (2020). Improving Climate Change Mitigation Analysis: A Framework for Examining Feasibility. One Earth *3*, 325-336. https://doi.org/10.1016/j.oneear.2020.08.007.

75. Moallemi, E.A., Eker, S., Gao, L., Hadjikakou, M., Liu, Q., Kwakkel, J., Reed, P.M., Obersteiner, M., Guo, Z., and Bryan, B.A. (2022). Early systems change necessary for catalyzing long-term sustainability in a post-2030 agenda. One Earth. 10.1016/j.oneear.2022.06.003.

76. Eker, S., Reese, G., and Obersteiner, M. (2019). Modelling the drivers of a widespread shift to sustainable diets. Nat. Sustain. *2*, 725-735. 10.1038/s41893-019-0331-1.

77. Hadjikakou, M. (2017). Trimming the excess: environmental impacts of discretionary food consumption in Australia. Ecol. Econ. *131*, 119-128. http://dx.doi.org/10.1016/j.ecolecon.2016.08.006.

78. Reynolds, C., Goucher, L., Quested, T., Bromley, S., Gillick, S., Wells, V.K., Evans, D., Koh, L., Carlsson Kanyama, A., Katzeff, C., et al. (2019). Review: Consumption-stage food waste reduction interventions – What works and how to design better interventions. Food Policy. https://doi.org/10.1016/j.foodpol.2019.01.009.

79. Gatto, A., and Chepeliev, M. (2024). Global food loss and waste estimates show increasing nutritional and environmental pressures. Nat. Food. 10.1038/s43016-023-00915-6.

80. Gephart, J.A., Henriksson, P.J.G., Parker, R.W.R., Shepon, A., Gorospe, K.D., Bergman, K., Eshel, G., Golden, C.D., Halpern, B.S., Hornborg, S., et al. (2021). Environmental performance of blue foods. Nature *597*, 360-365. 10.1038/s41586-021-03889-2.

81. Humpenöder, F., Bodirsky, B.L., Weindl, I., Lotze-Campen, H., Linder, T., and Popp, A. (2022). Projected environmental benefits of replacing beef with microbial protein. Nature *605*, 90-96. 10.1038/s41586-022-04629-w.

82. Pikaar, I., Matassa, S., Bodirsky, B.L., Weindl, I., Humpenöder, F., Rabaey, K., Boon, N., Bruschi, M., Yuan, Z., van Zanten, H., et al. (2018). Decoupling Livestock from Land Use through Industrial Feed Production Pathways. Environ. Sci. Techno. *52*, 7351-7359. 10.1021/acs.est.8b00216.

83. van Selm, B., Frehner, A., de Boer, I.J.M., van Hal, O., Hijbeek, R., van Ittersum, M.K., Talsma, E.F., Lesschen, J.P., Hendriks, C.M.J., Herrero, M., and van Zanten, H.H.E. (2022). Circularity in animal production requires a change in the EAT-Lancet diet in Europe. Nat. Food *3*, 66-73. 10.1038/s43016-021-00425-3.

84. Sandström, V., Chrysafi, A., Lamminen, M., Troell, M., Jalava, M., Piipponen, J., Siebert, S., van Hal, O., Virkki, V., and Kummu, M. (2022). Food system by-products upcycled in livestock and aquaculture feeds can increase global food supply. Nat. Food *3*, 729-740. 10.1038/s43016-022-00589-6.

85. Zanten, H.H.E.V., Mario, H., Ollie, V.H., Elin, R., Adrian, M., Tara, G., J., G.P., Christian, S., and M., D.B.I.J. (2018). Defining a land boundary for sustainable livestock consumption. Glob. Chang. Biol. *24*, 4185–4194. doi:10.1111/gcb.14321.

86. Resare Sahlin, K., Gordon, L.J., Lindborg, R., Piipponen, J., Van Rysselberge, P., Rouet-Leduc, J., and Röös, E. (2024). An exploration of biodiversity limits to grazing ruminant milk and meat production. Nat. Sustain. *7*, 1160-1170. 10.1038/s41893-024-01398-4.

87. Herzon, I., Mazac, R., Erkkola, M., Garnett, T., Hansson, H., Jonell, M., Kaljonen, M., Kortetmäki, T., Lamminen, M., Lonkila, A., et al. (2024). Both downsizing and improvements to livestock systems are needed to stay within planetary boundaries. Nat. Food *5*, 642-645. 10.1038/s43016-024-01030-w.

88. Chang, J., Peng, S., Yin, Y., Ciais, P., Havlik, P., and Herrero, M. (2021). The Key Role of Production Efficiency Changes in Livestock Methane Emission Mitigation. AGU Advances *2*, e2021AV000391. https://doi.org/10.1029/2021AV000391.

89. FAOSTAT (2024). Cereal yields (1961-2022).

90. Jägermeyr, J., Müller, C., Ruane, A.C., Elliott, J., Balkovic, J., Castillo, O., Faye, B., Foster, I., Folberth, C., Franke, J.A., et al. (2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nat. Food. 10.1038/s43016-021-00400-y.

91. Rezaei, E.E., Webber, H., Asseng, S., Boote, K., Durand, J.L., Ewert, F., Martre, P., and MacCarthy, D.S. (2023). Climate change impacts on crop yields. Nat. Rev. Earth Environ. *4*, 831-846. 10.1038/s43017-023-00491-0.

92. Chang, J., Havlík, P., Leclère, D., de Vries, W., Valin, H., Deppermann, A., Hasegawa, T., and Obersteiner, M. (2021). Reconciling regional nitrogen boundaries with global food security. Nat. Food *2*, 700-711. 10.1038/s43016-021-00366-x.

93. Metson, G.S., Chaudhary, A., Zhang, X., Houlton, B., Oita, A., Raghuram, N., Read, Q.D., Bouwman, L., Tian, H., Uwizeye, A., and Eagle, A.J. (2021). Nitrogen and the food system. One Earth *4*, 3-7. https://doi.org/10.1016/j.oneear.2020.12.018.

94. FAO (2023). Achieving SDG 2 without breaching the 1.5 °C threshold: A global roadmap, Part 1 – How agrifood systems transformation through accelerated climate actions will help achieving food security and nutrition, today and tomorrow, In brief. Food and Agriculture Organization of the United Nations.

95. Schulze, M., Janssen, M., and Aschemann-Witzel, J. (2024). How to move the transition to sustainable food consumption towards a societal tipping point. Technol. Forecast. Soc. Change *203*, 123329. https://doi.org/10.1016/j.techfore.2024.123329.

96. Biesbroek, S., Kok, F.J., Tufford, A.R., Bloem, M.W., Darmon, N., Drewnowski, A., Fan, S., Fanzo, J., Gordon, L.J., Hu, F.B., et al. (2023). Toward healthy and sustainable diets for the 21st century: Importance of sociocultural and economic considerations. Proc. Natl. Acad. Sci. U.S.A. *120*, e2219272120. doi:10.1073/pnas.2219272120.

97. FAO. (2024). The State of Food and Agriculture 2024 10.4060/cd2616en.

98. Schulte-Uebbing, L.F., Beusen, A.H.W., Bouwman, A.F., and de Vries, W. (2022). From planetary to regional boundaries for agricultural nitrogen pollution. Nature *610*, 507-512. 10.1038/s41586-022-05158-2.

99. Arndt, C., Hristov, A.N., Price, W.J., McClelland, S.C., Pelaez, A.M., Cueva, S.F., Oh, J., Dijkstra, J., Bannink, A., Bayat, A.R., et al. (2022). Full adoption of the most effective strategies to mitigate methane emissions by ruminants can help meet the 1.5 °C target by 2030 but not 2050. Proc. Natl. Acad. Sci. U.S.A. *119*, e2111294119. doi:10.1073/pnas.2111294119.

100. Havlík, P., Valin, H., Herrero, M., Obersteiner, M., Schmid, E., Rufino, M.C., Mosnier, A., Thornton, P.K., Böttcher, H., Conant, R.T., et al. (2014). Climate change mitigation through livestock system transitions. Proc. Natl. Acad. Sci. U.S.A. *111*, 3709-3714. 10.1073/pnas.1308044111.

101. Leroy, F., and Ederer, P. (2023). The Dublin Declaration of Scientists on the Societal Role of Livestock. Nat. Food *4*, 438-439. 10.1038/s43016-023-00784-z.

102. Bryant, C., Aiking, H., Alessandrini, R., Behrens, P., Creutzig, F., Eshel, G., Green, R., Hutchings, N., Leip, A., Milo, R., et al. (2024). The Dublin Declaration fails to recognize the need to reduce industrial animal agriculture. Nat. Food *5*, 799-801. 10.1038/s43016-024-01054-2.

103. Blackstone, N.T., Battaglia, K., Rodríguez-Huerta, E., Bell, B.M., Decker Sparks, J.L., Cash, S.B., Conrad, Z., Nikkhah, A., Jackson, B., Matteson, J., et al. (2024). Diets cannot be sustainable without ensuring the well-being of communities, workers and animals in food value chains. Nat. Food *5*, 818-824. 10.1038/s43016-024-01048-0.

104. Benton, T.G., Beddington, J., Thomas, S.M., Flynn, D.J., Fan, S., and Webb, P. (2021). A ‘net zero’ equivalent target is needed to transform food systems. Nat. Food. 10.1038/s43016-021-00434-2.

105. Sutton, M.A., Howard, C.M., Kanter, D.R., Lassaletta, L., Móring, A., Raghuram, N., and Read, N. (2021). The nitrogen decade: mobilizing global action on nitrogen to 2030 and beyond. One Earth *4*, 10-14. 10.1016/j.oneear.2020.12.016.

106. Weindl, I., Soergel, B., Ambrósio, G., Daioglou, V., Doelman, J.C., Beier, F., Beusen, A., Bodirsky, B.L., Bos, A., Dietrich, J.P., et al. (2024). Food and land system transformations under different societal perspectives on sustainable development. Environ. Res. Lett.

107. van Vuuren, D.P., Zimm, C., Busch, S., Kriegler, E., Leininger, J., Messner, D., Nakicenovic, N., Rockstrom, J., Riahi, K., Sperling, F., et al. (2022). Defining a sustainable development target space for 2030 and 2050. One Earth. https://doi.org/10.1016/j.oneear.2022.01.003.

108. Fanzo, J., Haddad, L., Schneider, K.R., Béné, C., Covic, N.M., Guarin, A., Herforth, A.W., Herrero, M., Sumaila, U.R., Aburto, N.J., et al. (2021). Viewpoint: Rigorous monitoring is necessary to guide food system transformation in the countdown to the 2030 global goals. Food Policy *104*. 10.1016/j.foodpol.2021.102163.

109. United Nations Environment Programme and Climate and Clean Air Coalition (2021). Global Methane Assessment: Benefits and Costs of Mitigating Methane Emissions. United Nations Environment Programme. https://www.unep.org/resources/report/global-methane-assessment-benefits-and-costs-mitigating-methane-emissions.

110. Porkka, M., Virkki, V., Wang-Erlandsson, L., Gerten, D., Gleeson, T., Mohan, C., Fetzer, I., Jaramillo, F., Staal, A., te Wierik, S., et al. (2024). Notable shifts beyond pre-industrial streamflow and soil moisture conditions transgress the planetary boundary for freshwater change. Nature Water *2*, 262-273. 10.1038/s44221-024-00208-7.

111. Gerten, D., and Kummu, M. (2021). Feeding the world in a narrowing safe operating space. One Earth *4*, 1193-1196. https://doi.org/10.1016/j.oneear.2021.08.020.

112. Beyer, R.M., Hua, F., Martin, P.A., Manica, A., and Rademacher, T. (2022). Relocating croplands could drastically reduce the environmental impacts of global food production. Commun. Earth Environ. *3*, 49. 10.1038/s43247-022-00360-6.

113. Davis, K.F., Rulli, M.C., Seveso, A., and D'Odorico, P. (2017). Increased food production and reduced water use through optimized crop distribution. Nat. Geosci. *10*, 919–924. 10.1038/s41561-017-0004-5.

114. Alexander, P., Reddy, A., Brown, C., Henry, R.C., and Rounsevell, M.D.A. (2019). Transforming agricultural land use through marginal gains in the food system. Glob. Environ. Chang. *57*, 101932. https://doi.org/10.1016/j.gloenvcha.2019.101932.

115. Béné, C. (2022). Why the Great Food Transformation may not happen–A deep-dive into our food systems' political economy, controversies and politics of evidence. World Development *154*, 105881.

116. Brutschin, E., Pianta, S., Tavoni, M., Riahi, K., Bosetti, V., Marangoni, G., and van Ruijven, B.J. (2021). A multidimensional feasibility evaluation of low-carbon scenarios. Environ. Res. Lett. *16*, 064069. 10.1088/1748-9326/abf0ce.

117. Baldos, U.L.C., and Hertel, T.W. (2016). Debunking the 'new normal': Why world food prices are expected to resume their long run downward trend. Glob. Food Sec. *8*, 27-38. https://doi.org/10.1016/j.gfs.2016.03.002.

118. Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., and The, P.G. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med. *6*, e1000097. 10.1371/journal.pmed.1000097.

119. Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., et al. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ *372*, n71. 10.1136/bmj.n71.

120. van Dijk, M., Morley, T., Rau, M.L., and Saghai, Y. (2021). A meta-analysis of projected global food demand and population at risk of hunger for the period 2010–2050. Nat. Food *2*, 494-501. 10.1038/s43016-021-00322-9.

121. Stein, W.E., and Keblis, M.F. (2009). A new method to simulate the triangular distribution. Math. Comput. Model. *49*, 1143-1147. https://doi.org/10.1016/j.mcm.2008.06.013.

122. Pendrill, F., Gardner, T.A., Meyfroidt, P., Persson, U.M., Adams, J., Azevedo, T., Bastos Lima, M.G., Baumann, M., Curtis, P.G., De Sy, V., et al. (2022). Disentangling the numbers behind agriculture-driven tropical deforestation. Science *377*, eabm9267. doi:10.1126/science.abm9267.

123. Hosonuma, N., Herold, M., De Sy, V., De Fries, R.S., Brockhaus, M., Verchot, L., Angelsen, A., and Romijn, E. (2012). An assessment of deforestation and forest degradation drivers in developing countries. Environ. Res. Lett. *7*, 044009. 10.1088/1748-9326/7/4/044009.

124. Diniz Oliveira, T., Brunelle, T., Guenet, B., Ciais, P., Leblanc, F., and Guivarch, C. (2021). A mixed-effect model approach for assessing land-based mitigation in integrated assessment models: A regional perspective. Glob. Chang. Biol. *27*, 4671-4685. https://doi.org/10.1111/gcb.15738.

125. Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting linear mixed-effects models using lme4. J. Stat. Softw. *67*, 1-48. 10.18637/jss.v067.i01.

126. Tredennick, A.T., Hooker, G., Ellner, S.P., and Adler, P.B. (2021). A practical guide to selecting models for exploration, inference, and prediction in ecology. Ecology *102*, e03336. https://doi.org/10.1002/ecy.3336.

127. Olsen, L.R., Zachariae, H.B., Patil, I., and Lüdecke, D. (2022). cvms: Cross-Validation for Model Selection. R package version 1.3.7.

128. Koller, M. (2016). robustlmm: An R Package for Robust Estimation of Linear Mixed-Effects Models. J. Stat. Softw. *75*, 1 - 24. 10.18637/jss.v075.i06.

129. Tremblay, A., and Ransijn, J. (2020). LMERConvenienceFunctions: Model Selection and Post-hoc Analysis for (G)LMER Models. R package version 3.0. Statistics Canada & University of Copenhagen.

130. Barton, K. (2019). MuMIn: Multi-Model Inference. R package version 1.43.6.

131. Nakagawa, S., and Schielzeth, H. (2013). A general and simple method for obtaining R2 from generalized linear mixed-effects models. *4*, 133-142. doi:10.1111/j.2041-210x.2012.00261.x.

132. Knowles, J.E., Frederick, C., and Whitwirth, A. (2020). merTools: Tools for Analyzing Mixed Effect Regression Models}.

133. FAO (2024). The State of Food and Agriculture 2024 – Value-driven transformation of agrifood systems. Food and Agriculture Organization of the United Nations.

134. Tilman, D., and Clark, M. (2014). Global diets link environmental sustainability and human health. Nature *515*, 518-522. http://dx.doi.org/10.1038/nature13959.

135. Lassaletta, L., Billen, G., Garnier, J., Bouwman, L., Velazquez, E., Mueller, N.D., and Gerber, J.S. (2016). Nitrogen use in the global food system: past trends and future trajectories of agronomic performance, pollution, trade, and dietary demand. Environ. Res. Lett. *11*, 095007.

136. Mueller, N.D., Lassaletta, L., Runck, B.C., Billen, G., Garnier, J., and Gerber, J.S. (2017). Declining spatial efficiency of global cropland nitrogen allocation. Global Biogeochem. Cycles *31*, 245-257. 10.1002/2016gb005515.

Supplemental Information for

Ambitious food system interventions required to mitigate the risk of exceeding Earth's environmental limits

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Table of Contents

1 Supplemental items

1.1 Note S1 - 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 [1-3]. We followed the guidelines for systematic reviews and meta-analysis in ecology and environmental management [4-8], 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 [9-13]. Evidence of all search strings, search results, and data extracted is provided in Data S1 and Data S2.

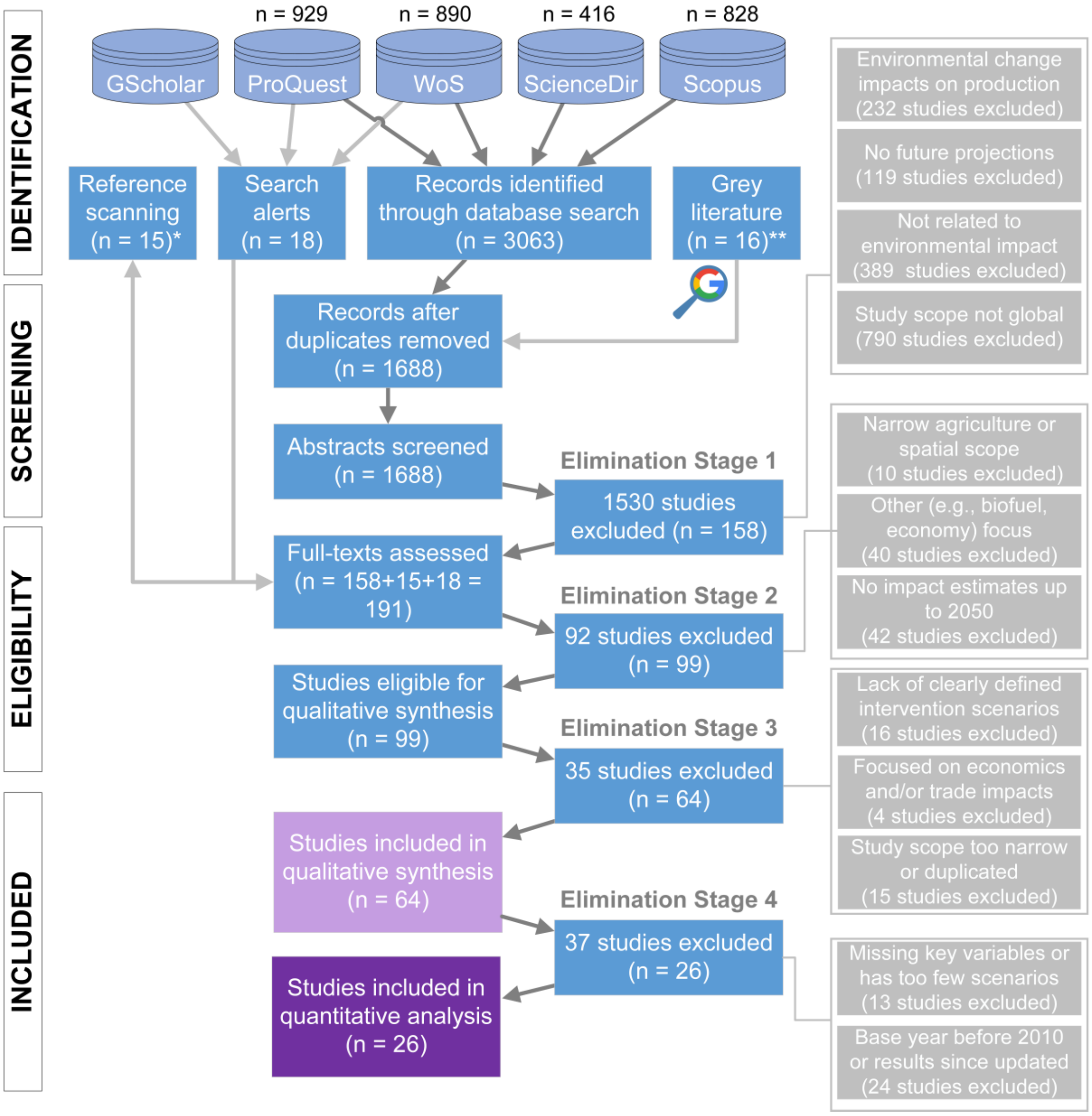


Fig. S1. Summary of the literature search and the study identification and screening process following the PRISMA protocol [9,13] (see Data S2 for full study details).

* Includes grey literature

** Excludes grey literature identified through reference scanning

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 and a time horizon of at least up to 2050.
2. To develop a meta-regression model to quantify the technical risk mitigation potential of the future global food system exceeding key environmental limits [14-17] under different food system scenario intervention combinations.
3. To extract qualitative information on the necessary actions that enable different food system interventions.

Given the broad 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 [7]. Framing of the research question was defined using the Problem-Intervention-Comparator-Outcomes (PICO) framework [7,18]:

- Problem: the future environmental impact (across key environmental limits) 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 to studies that estimate global-scale environmental impacts associated with land-based food production, including inputs to aquaculture but excluding 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 (scenarios with 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 are commonly based on status quo or trend projections of population growth, or agricultural efficiency and diets.
- Outcomes: meta-regression models capable of estimating the effect size and risk mitigation potential of key food system interventions for environmental indicators representative of key environmental limits.

1.1.3 Literature search

We identified primary research published in peer-reviewed journal articles and grey literature (major reports) containing quantitative estimates of future food system environmental impacts of relevance to environmental limits. 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 (see 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 initial search string was then adapted to three other scholarly databases (Scopus, Web of Science – Core Collection, Science Direct – All Sciences) and implemented from October to November, 2017. The search was restricted to peer-reviewed scholarly journal papers, conference proceedings, and book chapters. The use of multiple reputable online databases ensured comprehensiveness [19]. Search alerts were also set up using the final search string and the carefully assembled team of study co-authors covering many key institutions across different continents were engaged throughout this period to ensure that any new articles were included. This allowed for periodic updates through to the end of November 2024. An updated systematic search (using a modified search string) was run on 04 December 2024 to ensure that all relevant literature was captured.

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 performance of the search strategy relative to the test list [10]. The search was based on four concepts:

1. Relevance to some aspect of the food system;
2. Inclusion of future scenarios;
3. Assessment of environmental impacts relating to key environmental limits, 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 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.

An anticipated challenge was to include relevant grey literature given its importance in this research space [3]. 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 relevant review article [20] was also used to identify additional reports from the grey literature (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. Strikethrough text and italic text indicates parts of the search string that were deleted or added respectively in the final search to further constrain the search strategy to relevant records.

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 land-based 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”)	Ensures that the focus is on global studies.
	NOT ti-ab(“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 "Nepal*" OR "Arab*" OR "Ira*" OR "Arct*" OR "Ital*" OR "Alp*" OR "Indonesia*" OR "Saudi" OR "temperate" OR "tropic*" OR "bay" OR "plateau" OR "Kazak*" OR "sub-tropical" OR "Kenya*" OR "Black Sea" OR "Carrib*" OR "Korea*" OR "Syria*" OR "Ethiopia*" OR "highlands" OR "Sea" OR "salin*" OR "permafrost" OR "Central Asia" OR "Malay*" OR "erosi*" OR "drought" OR "rainfall" OR "precip*" OR "flood*" OR "Atlant*" OR "Pacific*" OR "tundra*"*)	Excludes regional/local studies. Any studies with country or region name in the title have been eliminated (only possible in Scopus, Web of Science and ProQuest)

1.1.4 Article screening

After removal of duplicates, the titles and abstracts of the remaining 1688 studies 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 any future projections
- articles focusing on non-environmental aspects of the food system (e.g., food security, pest management)
- articles that were not global in scope or only covered one component of the food system (e.g., livestock) (Fig. S1, Data S2)

158 studies out of those identified in the initial database search were selected for full text screening. During full text screening, the reference lists of more recent articles and reports were used to identify other relevant articles through citation and reference scanning.

Over the course of the entire study, full text screening was carried out for a total of 191 studies including selected studies from the initial database search (158), and studies (journal articles, book chapter or reports) identified through reference scanning (15) and journal alerts (18) (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 elimination stage was carried out on the remaining 99 studies resulting in a total of 64 studies that met all inclusion criteria necessary for the qualitative synthesis (Data S1). The exclusion criteria were:

- lack of clearly defined intervention scenarios
- focus on economics and/or trade impacts
- studies focused on a narrower thematic scope such as a specific domain of the food system (e.g., livestock, biodiversity, fisheries) or findings duplicated in other more recent and more comprehensive studies (Fig. S1, Data S2)

The 64 studies remaining after the third elimination stage were included in the qualitative synthesis, but only 26 provided training data for the meta-regression models following strict data quality considerations in the model selection and fitting stage (Section 1.3.1). The following exclusion criteria were applied in the fourth elimination stage to select the 26 studies for inclusion in the quantitative analysis:

- Key variables not available or inconsistent with other studies and/or lack of sufficient data to parameter re-calculation
- Old base year (before 2010), or results fully covered by a similar or more recent study using the same model
- Environmental impact estimates not compatible with majority of studies (e.g., significantly different base year starting values)

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 or more of eight environmental indicators representing four key environmental limits [15,16] (see 1.2 for choice of indicators and limits). 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 (Data S1). This process was iterative since the primary objective was to establish a consistent set of interventions and their associated quantitative input variables (see 1.3.1). 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 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; Data S2). In close collaboration with invited co-authors, we also carried out additional calculations to harmonize the highly diverse data types (see 1.3; 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. When assembling the quantitative database (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 [5,19,21]. The extracted quantitative data (Data S1) was used to train the meta-regression models (see 0).

1.1.6 Study selection bias

Primary studies were selected based on whether they met the inclusion criteria (Section 1.1.4). To accommodate the diverse modelling approaches and storyline assumptions, we considered peer-reviewed studies and high-profile reports to be of high quality and the range of available scenarios was considered 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 [3] (Section 0). We also present sensitivity results that assess the impact of different models on pooled effect size estimates (Section 1.5.3).

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 [22]. 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 [5] 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 S4). However, reporting bias is likely to be significant in our study. While some authors did not report key input or output variables, other authors explicitly shared comprehensive supplementary information and multiple scenarios resulting from sensitivity analysis. While this source of bias could not be eliminated, we minimized data information loss by assembling a team of key study authors and working closely as a group to reconstruct and curate input datasets to ensure sufficient data quality and harmonisation acrss key variables (see Section 0; Data S1). Our extensive use of search alerts also allowed us to remain up-to-date with relevant publications.

1.2 Note S2 - Defining food system specific environmental limits

We specified environmental limits which quantify the food system's share of the Earth's safe operating space 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 four environmental domains for which agriculture is a major driver and for which consistent quantitative information is abundant across different studies and models, namely climate change, land use change, water use, and nutrient flows [17,23-25]. The choice of eight environmental indicators reflects current scientific consensus on relevant planetary boundaries (PBs) and safe Earth system boundaries (ESBs) [15-17,23-25], ensuring consistent and comparable data from available projections for our target year (2050). In each case we sought to extract as many indicators as possible to maximize the coverage of key environmental limits while ensuring adequate sample sizes to allow statistical analysis.

For each indicator we identified the best estimate for the safe global limit, along with minimum and maximum values based on a literature review of recently 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 [26-28]. Even in the case of , where a large number of scenario runs compliant with 1.5°C and 2.0°C targets were already available through the AR6 Scenarios Database [29], the triangular distribution provided a good approximation of the spread between the models.

Distributions were fitted to the best available data on food system specific environmental limits (see Table S2 for sources) with the R package *propagate* [30] 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 [31,32]. 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 [31,32]. 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).

In the case of time-sensitive planetary boundaries for which an agriculture-specific environmental limit for 2050 had not been specifically established [17], 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 agricultural area, GHG emissions, and surface water flows (Table S2). In the case of GHG emissions we focused on the agriculture component of Agriculture, Forestry, and Other Land Use (AFOLU) for 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 the IPCC AR6 database [29]. This provided targets for agriculture that are in harmony with storyline assumptions about the necessary decarbonization of the broader economy [33,34].

While we acknowledge that the values underpinning several global environmental limits remain the subject of considerable research and refinement [14], here we only considered selected global environmental limits that relate strongly to indicators commonly used as outputs in global food system scenario studies (see Section 1.6). Despite significant regional heterogeneities and uncertainties in proposed thresholds [15,35,36], adherence to global limits is a central premise of the PB and ESB frameworks [16]. To the extent possible, our food-system specific environmental limit estimates encompass the uncertainty in our scientific knowledge of the safe operating space for each indicator [16,17,23,25], 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 in relation to key planetary and earth system 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
			Agricultural area
TotalAgArea Total agricultural area (i.e., cropland + pasture)	<3,309 Mha (3,019 – 5,460)	[16,25,37]	The total land area under agriculture (i.e., cropland and pasture) serves as a proxy for the impact of the food system on the planetary boundary of land-system change. It relates strongly to the amount of forest cover remaining, with major forest biomes having a key role in land surface-climate coupling [16,23,25,38]. Following [37], 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) [25]. For consistency with the majority of the studies in our database and existing estimates [16,37], we source all figures from FAOSTAT [39], while acknowledging that other widely used cropland and pasture estimates [40] 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 [37], with a 75-54% (41.35 – 54.60 Mha) zone of uncertainty as suggested in [16,25]. In line with our overall methodology of deriving environmental limits that 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 [41], 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 [25] 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) [41-45]. In line with recent studies [23,46-49], 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. [41] 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 [43], and is consistent with older

Indicator	Env. limits (best estimate, low, high)	Sources	Rationale
			estimates from the 1980s and 1990s [44]. Based on similar data, Hosonuma et al. [42] calculate 73%, with the remainder attributed to mining (7%), infrastructure (10%), and urban expansion (10%). The more recent estimates in Curtis et al. [41] 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 [45]. We therefore defined the maximum share as 100%, as this is also in agreement with [50] who determined that the overwhelming majority (90-99%) of tropical deforestation occurs where agriculture is the dominant driver of tree cover loss. 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 area estimate and the more conservative 73% share (3019 Mha). The high estimate assumed 100% of the remaining boundary would be afforded to agriculture.
Surface water flows			
Water Water withdrawals by agriculture (surface water plus groundwater)	<6,308 km^3 yr^{-1} (1,033 – 8,558)	[15,51]	The original PB associated with water was termed 'freshwater use' and was assigned a global control variable of blue water consumption with a recommended boundary value of 4000 (4000-6000) km^3 yr^{-1} [52]. This value was subsequently used in several global food system assessments [17,23,25,53], in combination with basic assumptions around agriculture's share of water consumption in the future. In the latest iteration of the PBs [16], the boundary associated with water was revised to 'freshwater change'. The recommended control variables were defined as the % of global ice-free land area with significant deviations of streamflow (blue water) and soil moisture (green water) respectively, relative to pre-industrial times [54]. While the revised PB better reflects anthropogenic modifications across the entire water cycle, the suggested control variables are not compatible with our analysis given the unavailability of such bespoke land area estimates for our selected studies. Instead, we adopted the global safe Earth system boundary (ESB) for water [15] which specifies a globally aggregated volumetric surface flow alteration based on a sub-global safe ESB of 10-30% alteration of monthly surface water flows that allows the remainder (70-90%) of flows for meeting environmental flow requirements. As the authors acknowledge in their supplementary material [15], this global-scale volumetric aggregation allows comparisons to global accounting of blue water flows (withdrawals). This is directly comparable to the data on water withdrawals from selected studies. Compared to the PB for freshwater use, the safe ESB is based on revised estimates of annual runoff which reflect increased water accessibility due to human development and climate change, it has a stricter basin-level withdrawal limit (20% throughout the year versus previously 30-60% depending on the season), and, importantly, considers withdrawals as opposed to consumptive use [15]. The authors note a high confidence in a global surface water alteration budget of 7,630 km^3 yr^{-1}. This corresponds to 20% of the long-term global continental runoff estimate from the of 38,153 km^3 yr^{-1} from the water balance model (WBM) runs [55] using monthly climate forcings from TerraClimate [56] for the period 2000-2020. Based on supplementary information in [15], there is a range in global annual continental runoff across different studies which we used to derive an uncertainty range around this estimate. We also considered a possible range for withdrawal limits based on the underlying research that informed the safe ESB proposed in [15]. We adopted a stricter 10% of mean annual flow consistent with a high level of ecological protection of the riverine ecosystem to ensure the natural structure and function of riverine ecosystems [57], As the highest allowable estimate we used the 20% presumptive standard because there is evidence that alterations greater than 20% pose a moderate risk to aquatic organisms, ecosystem function and ecosystem services [15,58]. As our mean estimate we adopted 15% as the mid-point of a moderate level of protection (11-20%) which entails measurable changes in structure and minimal changes in ecosystem functions [57]. The minimum and maximum runoff estimates of 36,812 and 42,158 km^3 yr^{-1} translate to a global surface flow alteration estimate of 3,681 (assuming a 10% withdrawal limit) and 8,432 km^3 yr^{-1} (assuming a 20%withdrawal limit) respectively. We therefore adopted a global surface water alteration budget of 5,723 (3,681-8,432) km^3 yr^{-1}. Based on future water resources projections across economic sectors, we adjusted the overall limit to accommodate non-agriculture needs, a notion also compatible with

Indicator	Env. limits (best estimate, low, high)	Sources	Rationale
			[59]. The range in projected water withdrawals by other higher value water users such as industry and households [45,60,61] reduces the safe operating space for agriculture. Unlike previous studies [17,53], 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 use, with both water demand from both of these sectors expected to increase much more rapidly compared to irrigation demand [62,63]. Several studies have estimated future non-agricultural water withdrawals [62-68]. Using estimates from 27 scenarios across five studies published in the last 10 years that have produced estimates of 2050 non-agricultural water withdrawals [62,63,68-70], we calculated minimum, average and maximum estimates for non-agricultural blue water withdrawals in 2050 (min = 1010, mean = 1,948, max = 2,876). These were then subtracted from the triangular distribution of the safe ESB (min = 3,681, max = 8,432, mode = 5,723) to yield a most likely estimate of 3,775 (805 to 7,422) km^3 yr^{-1}. The global surface water ESB is not fully compatible with data from our selected studies that specify total (surface and groundwater) withdrawals for agriculture. Since water demand is not solely satisfied through surface water alone, and since groundwater is covered by its own dedicated ESB which sums to 15,800 km^3 yr^{-1} global drawdown [15], we needed to make assumptions about the relative contributions of surface water and groundwater. Historically, groundwater has made a significant contribution of up to 35% of water withdrawals across all economic sectors [71]. However, recent work [72] highlighted the increasing use of unsustainable groundwater for irrigation purposes. Given these concerns around overuse of subsurface waters, and the high and increasing cost of groundwater pumping [73], surface water is likely to remain the preferred primary source for most uses [74]. Based on simulations of groundwater withdrawals across 235 water basins under 900 future scenarios of global change, Niazi et al. [51] estimates that groundwater withdrawals are expected to peak around mid-century at around 625 km^3 yr^{-1} (min = 228, max = 1136, where minimum and maximum correspond to the 5% and 95% quantiles respectively in Figure 1 in [51]). When considering the extent of contribution of groundwater to agricultural water withdrawals, the final environmental limit for water withdrawals by agriculture (surface water plus groundwater) is 4,400 (1,033-8,558) km^3 yr^{-1}. This limit encompasses only risk to surface water resources at the global level. It does not explicitly account for potential exceedances to sub-global surface water or groundwater limits.
Greenhouse gas emissions			
NonCO₂LUC Direct on-farm non-CO_2 (CH_4 + N_2O) + net emissions from land-use and land-use change	<3.53 $GtCO_2e$ yr^{-1} (SD = 3.52) *Estimated using AR6 GWP100 factors*	29	The food system is an important driver of climate change. Agriculture is one of the dominant sources of anthropogenic CH_4 and N_2O emissions. It is also a key driver of CO_2 emissions associated with land-use change processes such as deforestation and destruction of peatlands for agricultural purposes [75]. 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 [76-78]. Given the dominant role of fossil fuels, agriculture is not the main driver of CO_2 emissions [23]. The remaining carbon budget (dominated by CO_2 emissions) compatible with meeting climate targets (i.e. 2ºC or 1.5ºC) must be shared across all economic sectors. While mitigation measures in the food system have considerable technical potential ensure the food system achieves ambitious decarbonisation [75,79], agriculture's share of the global carbon budget varies across 2ºC or 1.5ºC compliant IPCC scenarios depending on how other key sectors (especially energy and transport) decarbonise [29,80-82]. Studies have proposed agriculture-specific or food system specific 2050 targets in line with a 2ºC or 1.5ºC temperature change target [17,34,37,80]. With the exception of [34], 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 [83]. For compatibility with the other environmental limits, we selected a total of 260 target-compliant scenarios from the AR6 Scenarios Database [29] and fitted a triangular distribution to all compliant scenario projections to establish a direct non-CO_2 annual GHG emissions range for agriculture in 2050. We use standard AR6 GWP-100 factors in our calculations, with a value of 27.2 and 273 for CH_4 and N_2O respectively. Many models and studies calculate net CO_2 emissions from land-use change alongside direct non-CO_2 emissions, with their sum constituting a major component of the AFOLU classification of national GHG inventories [84]. 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 [29], 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$_2$LUC* 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 [85-87]. We acknowledge that our climate change limits only cover 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 [46]. A number of studies that use GHG data from life-cycle assessments [34,88-90] 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.
Nutrient cycles: Nitrogen & Phosphorus			
N$_{fert}$ Total nitrogen fertilizer application in agriculture	<69 TgN yr^{-1} (52-113)	[17]	The global PB for the N cycle as defined in [16,24,25] is supposed to act as a global "valve" limiting new reactive N entering the Earth system which risks triggering irreversible hypoxic events in the ocean. The control variable is the global sum of all intentional fixation (i.e., industrial plus anthropogenic biological fixation by leguminous crops) and the suggested threshold value is 62 (62-82) TgN yr^{-1}. The current global value for biological fixation is a highly uncertain parameter, with estimates ranging from 30 to 70 TgN yr^{-1} [116]. Most of the selected studies provide estimates only for industrial N fixation associated with fertilisers. The large variation in biological fixation may be explained by the considerable differences in scope. In studies where this has been restricted to cropland and intensive pasture (thus excluding extensive pastures), the estimates tend to be at the lower end [15,91]. Recent studies [35,91] emphasise the importance of considering surplus (defined as total N input minus crop or grass N removal) as opposed to new fixation, since it is the surplus N after harvest that directly determines N losses to water and the atmosphere, thus contributing to issues such as eutrophication and degradation of terrestrial ecosystems. However, as is the case with biological fixation, the different scopes of studies (i.e., coverage of intensive or extensive grassland) mean that base year (2010) surplus estimates from our study sample vary significantly, with a range of 112 to 159 TgN yr^{-1}. The estimate of 119 in [15,91] is at the lower end of this range. This is likely because it excludes surplus from extensive grassland. While the ESB estimates in [15,91] represent the most recent and comprehensive analysis of safe boundaries for agricultural N, these are fundamentally based on agricultural surplus and loss. Even though the authors provide estimates of corresponding global inputs (assuming a fixed a biological fixation value of 31 TgN yr^{-1}) and therefore allow the determination of a fertilizer only threshold of 62 (34-76) TgN yr^{-1} depending on whether only surface water eutrophication or also groundwater nitrate concerns are accounted for, this estimate implicitly assumes static (current) nitrogen use efficiency (NUE). As some of our model predictions entail significant changes in NUE and recycling, we adopted a PB estimate specific to N fertilizer that is also consistent with scenarios of change as per [17]. The slightly more recent estimate in [53] includes biological fixation and was therefore not considered. The final PB estimate of 67 (52-113) TgN yr^{-1} for nitrogen (N) fertilizer application represented a considerable upward revision of the PB in [25] which also includes biological fixation. This was based on updated modelling in [17] which made an allowance for potentially higher application of N that allows for the increased use of fertilizer if N is globally redistributed and efficiency of use is improved. In accordance with the precautionary principle, by using 52 TgN yr^{-1} as the minimum estimate, we also accounted for conservative future scenarios where improved production and redistribution practices are not adopted [92]. As these limits are already agriculture-specific, given also that agriculture's share of total global anthropogenic N is currently estimated at 90% [15], no further adjustment was performed.
P$_{fert}$ Total phosphorus fertiliser application in agriculture	<16.0 TgP yr^{-1} (6.0-17.0)	[15,17,53]	Similarly to the global PB for the N cycle, the global PB for the P cycle has remained unchanged in [16]. This PB has two control variables: P flow from freshwater systems into the ocean, and P flow from fertilisers to erosible soils. While the threshold for the former is set at a level that avoids global ocean anoxia, the latter is more relevant for freshwater eutrophication. It is the latter control variable that is most aligned to estimates of mineral P fertiliser application in agriculture from the selected studies, with only a few studies providing highly variable P surplus estimates.

The PB approach [16,25] assumes that the principal source of P to surface waters is soil erosion. According to [15], this neglects internal P inputs by manure and human waste following animal and human consumption and does not account for potential improvements in food chain PUE and enhanced P recycling. As we did for N_{fert}, we therefore adopted an estimate for P that allows a global rebalancing of P use through increases in P inputs in under-fertilised regions and reductions of P inputs in over-fertilised regions, while also ensuring that critical concentration limits of 50-100 mgP/m^3 for surface water are respected to prevent eutrophication.

We adopted the mode and maximum of 16 and 17 TgP yr^{-1} respectively directly from [15,17]. In line with the precautionary principle, as the lower boundary we adopted 6.0 which represents a worst-case scenario where 50% recycling and the redistribution assumed in the mode and maximum values as per [15,17,53]} are not adopted. As is the case for N_{fert}, this boundary is inherently agriculture-specific [15] thus requiring no additional adjustments.

1.3 Note S3 - Review of interventions, study selection and harmonization

1.3.1 Mapping key interventions to specific quantitative variables

An important prerequisite for training meta-regression models for each environmental indicator (Section 0) was compiling a comprehensive dataset of interventions as predictor variables and their impact on different environmental indicators (Table S3).

To identify major interventions, we first reviewed and mapped all on-ground mitigation actions suggested in the 64 studies selected for qualitative synthesis (see 1.1, Table S3). We first performed 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 diverse set of actions of varying specificity. We consulted references for additional detail and summarized the more than 200 specific on-ground mitigation actions to 58 by combining overlapping ones into a more comprehensive action (e.g., reduced tillage and residue retention were grouped into a single action called soil conservation). We grouped the final set of on-ground mitigation actions into five categories according to [88] (Data S3).

Table S3. All selected studies, environmental indicators (Section 0), and interventions (see 1.4.2). 'Y' = included in meta-regression models, 'N' = excluded from meta-regression models (see Table S4). 'T' = Trend/BAU projection, 'X' mitigation in excess of trend, 'V' = mitigation in excess of trend including vegan/vegetarian (Diet column only). Emissions intensity refers to reductions in non-CO_2 (CH_4 & N_2O) emissions intensity, while climate action (LUC) indicates explicit modelling of efforts to protect and restore natural ecosystems including through a carbon price.

Study details			Environmental limits & indicators											Interventions										
			GHG emissions			Agricultural area				Nutrient cycles				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	Emissions intensity	Climate action (LUC)	Water use efficiency	N & P use efficiency	N & P recycling
1	Davis et al. (2016)	Y				Y	Y		N	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)	N				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)	N								Y	Y	Y	Y	T	-			T	T				T	X
10	Damerau et al. (2016)	N							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)	N				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)	N				Y	Y	Y	Y					T	X		X							
22	Mogollon et al. (2018a)	N								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)	N	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)	N								Y		Y		T	X		X	X		X			X	
33	IAASTD (2009)	N				Y	Y		Y					T	-		X							

Study details			Environmental limits & indicators												Interventions										
			GHG emissions			Agricultural area				Nutrient cycles					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	Emissions intensity	Climate action (LUC)	Water use efficiency	N & P use efficiency	N & P recycling
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)	N								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		
41	Ercin & Hoekstra (2014)	N							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		
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)	N	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
61	van Vuuren et al. (2021)	Y	Y	Y	Y	Y	Y	Y		Y	Y			X	X	X	X	X	T	X	X		X	
62	Graham et al. (2023)	Y							Y					T	T	T	X	T	T			X		
63	Doelman et al. (2022)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y			T	X	X	X	X	T	X	X	X	X	
64	Kyle et al. (2023)	N	Y	Y	N	Y			Y	Y	Y	Y	Y	T	X	T	X	T	T	X	X	T		

* $N_{surplus}$ and $P_{surplus}$ were not calculated in a consistent way across studies (due to differences in scope, e.g., some included surplus from grassland while others only covered surplus from cropland) and were therefore not selected as indicators for further analysis.

While it was not possible to capture the entire range and diversity of available on- and off-farm mitigation actions with our chosen set of interventions and predictors, we considered those most influential and commonly assessed in food system scenario studies [20,53,93-96]. We then mapped the list of detailed on-ground actions to major interventions, each of which could be modelled based on a consistent set of quantitative variables available across studies (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 29 aggregated quantitative variables that could serve as proxies for modeling all major interventions (Table S4). Several studies had more detailed data that were subsequently aggregated to match the minimum set specified in Table S4. Some commonly applied or discussed interventions that could not be explicitly parameterized were organic agriculture, trade openness, and breakthrough technologies (e.g., cellular meat, novel feeds) (Data S1). These interventions or actions had insufficient data to be used as unique quantitative predictors, but their potential influence was partly controlled for through other variables such as crop yields, diet, feed efficiency, nutrient-use efficiency, and nutrient recycling.

Table S4. Minimum set of quantitative variables required to derive necessary predictors across all meta-regression models (see 0 for further explanation on metric selection and model fitting). For a complete list of data and variables see Data S1. FCR = feed conversion ratio, FCF = food-competing feed. Please note that for the N/P recycling intervention no variable was required since we apply an offset calculation only after the statistical prediction (see 1.4.2)

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
GHG emissions intensity	3	CH_4 intensity, N_2O intensity, carbon price	%Δ CH_4/N_2O, \$/tCO_2e
Water-use efficiency	1	Water withdrawals per unit of production	m^3/kg
N efficiency	1	Nutrient-use efficiency (outputs/inputs)	NUE (dimensionless)
P efficiency	1	Nutrient-use efficiency (outputs/inputs)	PUE (dimensionless)

1.3.2 Study selection and harmonization

Following a procedure similar to that described in [3] to control for the heterogeneity between model setups, studies or specific scenarios were excluded from the quantitative analysis based on a set of strict exclusion criteria (see elimination stage four in Fig. S1):

- **Too many missing/incompatible variables or assumptions**. This includes situations where variables from Table S4 were not available or had been calculated in very different units, and/or where insufficient information was provided on how to derive the necessary variables without resorting to any imputation of values based on questionable assumptions or external datasets. This includes studies that held pasture constant into the future [47], scenarios that assumed zero pasture contribution to animal feed [97].
- **Old base year (pre-2010) or older model version.** Studies with older base years or model versions tended to have different starting values across environmental indicators and input variables. Also, models have evolved over time to include a more comprehensive coverage of crops and livestock, more detailed biophysical processes and more detail in key intervention components such as diets and different efficiency parameters [98]. See 1.3.3 for further detail on base year harmonization.
- **Incompatible base year values**. Despite having a 2010 base year, some studies still had less complete system boundaries due to incomplete coverage of crops or emission sources. This was ascertained on an indicator-by-indicator basis in order to maximize sample sizes; in some instances, the scope coverage was comprehensive enough for land use indicators but not for emissions, as in the case of [99]. In some studies using the GLOBIOM model [35,100], cropland and non-CO_2 emissions were significantly lower compared to other studies and were therefore excluded on that basis (see Table S5).
- **Too few scenarios**. Where studies only had two or less scenarios [101,102] the studies were excluded on the basis that they did not have an adequate coverage of intervention variability.

Table S5. Justification for studies and scenarios excluded from the quantitative analysis. This follows the list above and the exclusion criteria for elimination stage four (Fig. S1).

Indicator	Excluded studies/scenarios	Justification(s)
All variables*	Lassaletta et al. (2016)	Too many missing/uncertain variables
	Schader et al. (2015)	Superseded by Muller et al. (2017)
	Alexandratos & Bruinsma (2012)	Only has a single future scenario
	Bennetzen et al. (2016)	Too many missing/uncertain variables
	Bodirsky et al. (2012)	Old base year (1995)
	Bodirsky et al. (2014)	Old base year (1995)
	Bouwman et al. (2013)	Old base year (2000)
	Damerau et al. (2016)	Did not calculate water withdrawal
	Lwin et al. (2017)	Too many missing/uncertain variables
	Odegard & van der Voet (2014)	Too many missing/uncertain variables
	Pfister et al. (2011)	Old base year (2000)
	Tilman et al. (2011)	Old base year (2005)
	Springmann et al. (2016)	GHG data out of scope
	Springer & Duchin (2014)	Too many missing/uncertain variables
	Heck et al. (2018)	Old base year (2005)
	Powell & Lenton (2012)	Old base year (2010)
	Stehfest et al. (2009)	Old base year (2000) and model version
	Metson et al. (2012)	Too many missing/uncertain variables
	Popp et al. (2010)	Old base year (1995) and model version
	Valin et al. (2013)	Old base year (2000) and model version
	Ronzon (2014)	Old base year (2000) and model version
	Pradhan et al. (2013)	GHG data out of scope
	Pradhan et al. (2015)	Too few scenarios and missing variables
	IAASTD (2009)	Old base year (2000)
	Wood et al. (2004)	Old base year (2000)
	PBL (2012)	Too many missing/uncertain variables
	Bouwman et al. (2009)	Old base year (2000)
	MEA (2005)	Old base year (1995)
	Popp et al. (2017)	Too many missing/uncertain variables
	UNCCD (2017)	Superseded by Doelman et al. (2018)
	Ercin & Hoekstra (2014)	Did not calculate water withdrawals
	Van Vuuren et al. (2010)	Old base year (2000) and model version
	Hejazi et al. (2014)	Old base year (2005) and model version
	Tallis et al. (2018)	Too many missing/uncertain variables
	Bahadur et al. (2018)	Cropland and GHG data out of scope
	Zhang et al. (2015)	Too few scenarios and missing variables
	Theurl et al. (2020)	Old base year (2000) and model version
	Page et al. (2023)	Too many missing/uncertain variables
Cropland	Bodirsky et al. (2014)	Cropland not an output of the modelling
	de Fraiture & Wichelns (2010)	Cropland not an output of the modelling
	Davis et al. (2016)	Modelled total area (crops + pasture)
	Roos et al. (2018) no pasture	All feed is from crops in these scenarios
	Muller et al. (2017)	Low base year value
	Weindl et al. (2017)	Low base year value
	Theurl et al. (2020)	Low base year value
Pasture	de Fraiture & Wichelns (2010)	Pasture not an output of the modelling
	Roos et al. (2018) no pasture	All feed is from crops in these scenarios
	Muller et al. (2017)	Constant pasture assumption
Water	Davis et al. (2016)	Did not calculate water withdrawal
Methane	FOLU (2019)	Low base year CH_4 outside AR6 range
	Chang et al. (2021)	Low base year CH_4 outside AR6 range
	Clark et al. (2020)	Low base year CH_4 outside AR6 range
	Theurl et al. (2020)	Low base year CH_4 outside AR6 range
	Roos et al. (2018) no pasture	All feed is from crops in these scenarios
	Searchinger et al. (2018)	Low base year CH_4 outside AR6 range
Nitrous oxide	Clark et al. (2020)	Fertiliser GHG scope includes upstream
	FAO (2018)	Low base year N_2O outside AR6 range
	Muller et al. (2017)	Low base year N_2O outside AR6 range
	Searchinger et al. (2018)	Low base year N_2O outside AR6 range
	Theurl et al. (2020)	Low base year N_2O outside AR6 range
	FOLU (2019)	Low base year CH_4 outside AR6 range
	Roos et al. (2018) no pasture	All feed is from crops in these scenarios
Nfert	Davis et al. (2016) efficiency	NUE metric is different from other studies
	Mogollon et al. (2018a)	Old base year (2005)
	Davis et al. (2016)	High base year value
Pfert	EAT-Lancet P recycling scenarios	These scenarios assume halving of Pfert

1.3.3 Base year harmonisation check

We followed an iterative process of carefully selecting studies based on strict exclusion criteria (see 1.3.2 & Table S5). During this process we also regularly checked the range and distribution of base year values for each of the environmental indicators as follows:

- **Acceptable base year ranges across indicators**. For the quantitative synthesis we only selected studies published in the last ten years (since 2014). This ensured that we only considered results from recent versions of models such as IMAGE 3.0 and 3.2, MAgPIE 3.0 (or later), GCAM 5.3 (or later), WITCH-GLOBIOM 3.1 (or later) which are considered comprehensive and contemporary enough to feature in the IPCC AR6 database[29,82]. The range in base year (2010) values for all variables therefore needed to be comparable to the range of IPCC AR6 for cropland, pasture, methane and nitrous oxide and for other key datasets used in the derivation of the environmental limits (Table S6). For CO_2 LUC, we directly used scenarios from integrated assessment models (IAMs) with comprehensive land-use models (LUMs) in the AR6 database: GCAM, IMAGE, MESSAGE-GLOBIOM, REMIND-MAgPIE, and WITCH-GLOBIOM (see 1.4.4).
- **Harmonization check**. We excluded studies with base years outside 2007-2012 to ensure a comparable scope (e.g., crop and livestock coverage, GHG emissions scope) and starting values for all environmental indicators. We also made sure starting values had <10% deviation from the reference base year value used to carry out predictions, thus also ensuring compatibility with the environmental limits (Table S2).
- **Statistical harmonization.** Despite our strict selection and harmonization efforts some level of variation persisted across starting values for different models. Additional statistical parameters such as the use of an initial condition delta [103] in combination with an appropriate effect size metric that measures relative change as opposed to absolute numbers were added to control for this (see 0).

Table S6. Base year (2010) values of selected models relative to the datasets used for harmonisation and those used to determine environmental limits. n = number of models.

Indicator	Units	Database	n	Mean	Min	Q_25	Q_75	Max
Cropland	Mha	This study	11	1547	1430	1545	1560	1601
		IPCC AR6 v1.1	35	1572	1458	1550	1585	1681
Pasture	Mha	This study	11	3273	3103	3254	3314	3379
		IPCC AR6 v1.1	31	3366	3186	3258	3456	3456
Water	$km^3 yr^{-1}$	This study	6	2636	2402	2542	2743	2889
		AQUASTAT (2015)	1	2700	-	-	-	-
CH_4	Mt CH_4	This study	9	145.9	138.3	141.5	150.4	154.7
		IPCC AR6 v1.1	37	154.9	138.9	148.4	165.9	168.2
N_2O	kt N_2O	This study	7	6689	6180	6223	6954	8022
		IPCC AR6 v1.1	36	7018	6404	6560	7731	8028
CO_2 LUC	Mt CO_2	This study	41	5460	2984	3765	6249	7162
		IPCC AR6 v1.1	41	5460	2984	3765	6249	7162
Nfert	Tg N yr^{-1}	This study	8	102.6	100.5	100.8	103.7	106.0
		Springmann et al. (2018)	1	103.7	-	-	-	-
Pfert	Tg P yr^{-1}	This study	6	18.0	17.4	17.8	18.2	18.8
		Springmann et al. (2018)	1	17.8	-	-	-	-

1.3.4 Additional calculations and harmonisation

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). Several published articles or reports did not report all relevant parameters (see Table S4) for each scenario. This required significant additional efforts to source and harmonize data to ensure compatibility between studies.

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.

1.3.5 Global weighted averages

The scope of our analysis is global. Where input parameters (see Table S4) 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:

$$x_{WORLD2050} = \sum_{i=1}^{n} \left(x_{i2050} * \frac{Pop_{i2050}}{Pop_{WORLD2050}} \right) \qquad \text{(Eq. S1)}$$

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 [17,53,77,97], 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 [104]. In cases where food demand was expressed in mass units, we used mass-to-calorie conversion factors calculated from [105] 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 1.4.2).

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

Given our focus on food and animal feed demand, our study scope and systematic 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 animal feed (see Fig. S1 and 1.1.4). However, several studies (or selected scenarios within studies) were based on scenario narratives that involved future demand changes in biofuels 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. S2) to control for any additional crop demand associated with biofuels and non-food crops on a study-by-study basis.

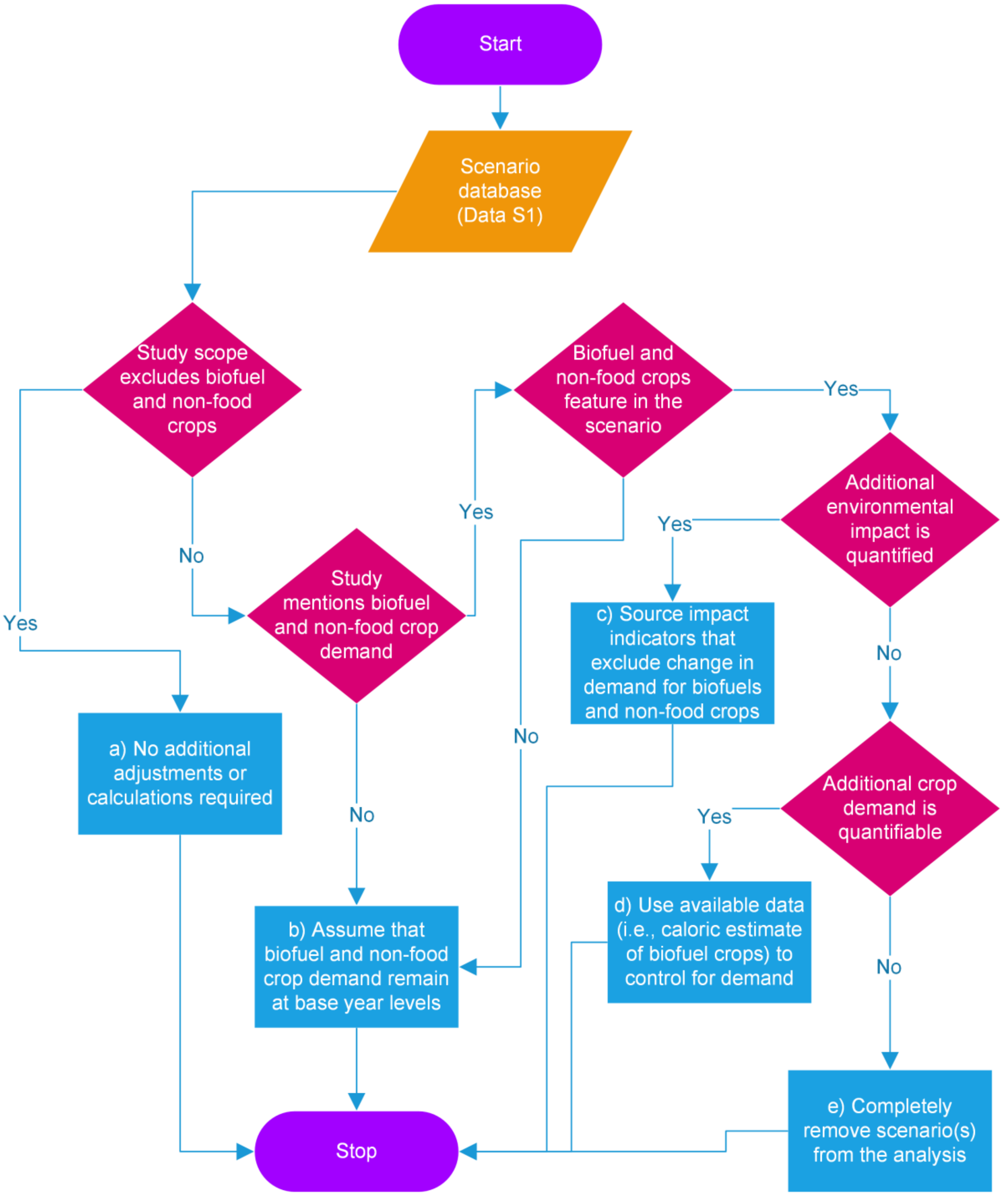


Fig. S2. Workflow diagram illustrating the steps followed to control for biofuel and non-food crop demand in relevant scenarios across all selected studies.

Following Fig. S2, the 26 studies that contained the full suite of necessary input and output data and were therefore eligible for training the meta-regression models (see Table S3 & Table S4) were classified as follows:

a) Five (5) studies [17,34,53,89,97] 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 (environmental indicators) or input variables.

b) Nine (9) studies [35,37,47,77,99,106-109] 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 narratives. 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 [109,110].
c) Ten (10) studies [69,76,100,111-116] included scenario narratives (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 [76,100,112].
d) Two (2) studies [68,117] 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 [105]. We note that in [68] 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) If additional demand for crops was not quantifiable, studies or scenarios were completely removed from the analysis. None of the studies or scenarios selected for quantitative analysis (Table S3) fell into this category.

1.3.7 Non-CO_2 GHG emission categories

Only studies that included the following breakdown in direct emission categories were included in the analysis (see Data S1 for full GHG emissions breakdown) to ensure consistency with with IPCC Agriculture in AR6 [29,83] and with FAOSTAT ‘within the farm gate’ emission categories [118,119]:

- CH_4 from enteric fermentation.
- CH_4 from rice cultivation.
- CH_4 from manure management
- N_2O from manure management
- N_2O associated with managed agricultural soils including synthetic fertilizers, biological fixation, manure left on pasture, manure applied to crops, crop residues and cultivated organic soils. Some studies included more aggregated categories encompassing multiple 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 [120]. 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 [118].

As shown in Table S6, the mean and range in base year (2010) CH4 and N2O values for selected studies/models is very close (within ~5%) to that seen in ARIAMs with comprehensive LUMs [29,83].

1.3.8 Alternative food system sustainability narratives

As part of our qualitative review of interventions, we also assessed the coverage of interventions across the 64 systematically selected studies (Table S3). Most studies combine interventions to create scenarios in a way that represents one or more of the prevailing sustainability worldviews [96,97,114]. Some worldviews and even individual interventions (e.g., reduction in food loss and waste, innovative technologies like novel proteins) may often combine demand- and supply- side elements (Table S7). Some studies intentionally focus on comparing scenarios that represent competing or complementary worldviews around food system sustainability [97,114,121]. Even studies that only model scenarios that adopt a similar worldview (e.g., sustainable intensification) may parameterise their scenarios and intervention levels differently depending on the focus (e.g., the environmental indicators of interest) of the study.

Table S7. 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 [110,122,123]	- Yield gap closure - Feed efficiency - Nutrient-use efficiency - Water-use efficiency		Production to distribution	- Nitrification inhibitors - Digital or precision agriculture
Circular economy [124-127]	- Nutrient recycling - Feed composition (reduction in food-competing feed) - Waste/loss reuse reduction		Production to distribution	- Livestock raised on waste or by-products
Agroecology [47,124]	- Organic production - Nutrient recycling - Ecological leftovers	Less but better meat Reduced waste	Production to consumption	- Crop rotations - Agro-forestry
Healthy and sustainable diets [17,53,89,128]		Reduction in animal protein Waste reduction Increased intake of fruits and vegetables	Retail and Consumption	- Taxes on ruminant meat - Education campaigns
Technological breakthroughs [97,125,130,131]	- 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

Food system sustainability narrative	Interventions		Supply chain stages impacted	Typical on-ground action example(s)
	Supply-side	**Demand-side**		
Degrowth [121,132]	- Regenerative/organic production - Sufficiency	- Ethical consumption - Sufficiency	Production to consumption	- Fairer income redistribution

1.3.9 Gaps in intervention coverage across studies and environmental limits

As a result of complex narratives giving rise to more integrated scenarios that combine multiple interventions, the coverage of interventions across studies and different environmental indicators (and environmental limits) is highly heterogeneous (Table S8). There was strong emphasis on diet change (75% of studies) and crop yields (71%) across all studies. Feed efficiency (47%) and food waste reduction (40%) followed in terms of study coverage, although a considerable percentage of studies focusing on water and nutrient cycles did not consider these interventions. Around 70% of studies across all environmental limits did not explicitly model interventions associated with changes in feed composition and their interaction with feed efficiency [133,134]. Similarly, 68% of studies did not consider population estimates beyond BAU trends, an issue highlighted in [135,136]. There is also generally a low coverage of resource-use efficiencies with the exception of nutrient cycles where nutrient-use efficiency is the key intervention [102].

Table S8. Coverage of all identified interventions across environmental limits. Cells show the percentage (shades of blue for >50% and shades of orange for <50%) of studies covering an environmental limit 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 (see Data S1 for more details and indicator-level breakdown).

	Environmental limits → **Interventions ↓**	GHG emissions	Agricultural area	Surface water flows	Nutrient cycles	All limits
Demand-side	Population	24%	21%	37%	46%	32%
	Diet change	95%	79%	68%	79%	75%
	Waste reduction	71%	55%	32%	54%	40%
Supply-side	Crop yields	90%	79%	63%	79%	71%
	Feed efficiency (FCR)	62%	52%	16%	54%	46%
	Feed composition	48%	33%	11%	33%	30%
	GHG emissions intensity *	86%	39%	26%	50%	37%
	Water-use efficiency	0%	0%	58%	0%	25%
	Nutrient-use efficiency	48%	0%	0%	79%	41%
	Nutrient recycling	19%	15%	11%	42%	24%
	# Studies	24	39	17	24	60
	% of reviewed studies	40%	65%	28%	40%	100%

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

1.4 Note S4 - Meta-regression modelling 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 eight chosen environmental indicators (see 1.2). The fitted meta-regression models were then used to create predictions in physical units (e.g., Gt CO_2e) for all combinations of interventions across ambition levels (see 1.4.2). The prediction intervals from the meta-regression models were subsequently compared to the PDFs representing each of the environmental limits (Table S2) 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 (see 1.1) and the insights gained from reviewing these studies and the wider literature to create a study-indicator-intervention matrix (Table S3) and a detailed table of actions (Data S3). These were then used as a basis to establish a set of key intervention strategies (Table S8) with the necessary underpinning quantitative variables to describe them (Table S4).

2. We fitted seven (7) independent linear mixed models (LMMs) for cropland, pasture, methane, nitrous oxide, water withdrawals, N_{fert} r and P_{fert}, 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 [137-140]. For each LMM, we tested alternative random effects structures using both random intercepts as well as slopes for the main fixed effect predictors. 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 composite indices (% change relative to the base year) from this minimum set of quantitative variables, in order to improve harmonization across all studies.

3. Following best practice for selecting predictive models [141,142], we carried out repeat K-fold cross-validation [143] of alternative random and fixed effect model structures to derive parsimonious process-based (aggregates of independent predictors e.g., total feed demand by livestock type) model structures, and selected the model with the best prediction skill (with the lowest RMSE) for each environmental indicator. Following cross-validation, we settled on the use of a simple random intercept model design with model ID as the random effect [3,144,145] for most indicators (cropland, pasture, N_{fert}, P_{fert}). A more complex random slope and random intercept structure[146] was used for water withdrawals, methane, and nitrous oxide.

4. Alternative levels of implementation ranging from low to very high mitigation ambition were then defined for each intervention strategy (see 1.4.2). We used the LMM with the highest predictive accuracy (lowest RMSE) to make predictions for the average group using the mean of the distribution μ_{group} [145] along with associated prediction intervals using the 'predictInterval' function in *merTools* [147] for each of the seven 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 S24). 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 v1.1[29], to fit an additional LMM to estimate emissions associated with land-use change (see 1.4.4). The land-use change model was then used to predict emissions associated with land-use change for the same consistent 2050 storylines using predictions from the cropland and pasture models as inputs.

5. We calculated aggregated estimates for agricultural area and emissions [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 [148]. We then computed the risk of exceeding environmental limits associated with each prediction by combining uncertainty in LMM predictions and uncertainty in environmental limits as represented by each corresponding probability density function (see 1.4.5). In the case of nutrient cycles, we calculated risk estimates separately for each of the indicators (N_{fert}, P_{fert}) as the distributions cannot be added together. 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 nutrient cycles. For surface water flows no further aggregation was required since it is only represented by a single indicator.
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 environmental limit following the one-at-a-time sensitivity analysis protocol described in [149]. We also carried out a similar calculation to estimate absolute change in physical units for each indicator (see Fig. S4).
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 environmental limits, and for all limits combined, yielding a total of 1,048,576 intervention level combinations (Fig. S5). We then selected the scenarios that met two critical IPCC-calibrated uncertainty risk thresholds [150,151] 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.

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 [99,136]. While many studies treated population growth as a scenario driver that was held constant across scenarios (Table S8), they still used different population projections for 2050 depending on their data sources and their date of publication. Some studies used established narratives such as the SSPs which include scenarios with significantly different population projections, with more environmentally sustainable scenarios generally associated with lower rates of population growth [99,152]. We selected a range of population levels to encompass the latest consensus of assumptions around key parameters likely to affect the extent of this intervention such as fertility, mortality, migration, and education from the UN World Population Prospects 2024 [153] and the SSP-Database 3.0 [154]. We used the following 4 levels (in order of increasing mitigation ambition):

- Low (10.093 billion) – This population estimate for 2050 corresponds to the SSP3 IIASA-WiC POP 2023 3.0 scenario [154] which assumes the highest rates of population growth as a result
- Trend (9.664 billion) – This corresponds to the 2024 UN DESA medium projection [153], reflecting the most likely trends in fertility, mortality, migration and education.
- High (9.455 billion) – This population estimate is an in-between estimate to fill the gap between Trend and Very high ambition. This trajectory results in a slightly lower 2050 estimate compared to SSP2 IIASA-WiC POP 2023 3.0 scenario [154].
- Very high (9.135 billion) – This corresponds to the SSP1 and SSP5 IIASA-WiC POP 2023 3.0 scenarios [154]. It assumes a rapid acceleration of the demographic transition due to very high educational and health investments [152,155].

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 focusing on the mitigation potential of healthy and sustainable diets [17,53,77,89]. 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 [17,53].
- Substitution – Diets where ruminant meat is partially substituted with monogastric meat, most commonly by 10 – 20% [156-159].
- Mediterranean – Diets rich in vegetables, fruit, seafood, grains, sugars, oils, eggs, dairy, and moderate amounts of meat [89,106].
- Dairy-based – Diets containing a much higher than average percentage of dairy products, some of which are assumed to replace ruminant meat [53,97].
- Pescatarian – Diets where animal protein is sourced predominantly from marine sources but still contain modest amounts of dairy/eggs [53,89,97,106]
- No meat – Vegetarian diets containing no meat [53,89,90,97,106,160-162] 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 1.6.4 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) [105]. 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 [105].

Modelled 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 [17,77] (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 [17], while values >2400 represent overconsumption [163]. 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} [164], 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 [105] along with nutrient content estimates from the USDA food composition database Standard Reference 28 [165], 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 [166] but the Low ASF variant falls short of the European Commission's 4 μg day^{-1} recommendation [167], 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 modelled diets, including the Low ASF + 1860 combination that corresponds to the flexitarian variant in the EAT-Lancet Commission [53], contain sufficient plant calories. We did not consider diets with zero meat or animal calorie intake due to their lower feasibility.

Table S9. 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 S10. 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 [114,168]. This pattern corresponds to current diets with a high share of calories from ASF such as those consumed in many developed countries [108,169-171].
- 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 [17,53,89,114,168]. This assumed ASF intake is representative of a nutrition transition [172] 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 [45,112], as well as other scenarios which assume more healthy and sustainable diets with reductions in ASF [77,107,108,114,117]. 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 [53,89,106].

- 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 [17,173]. Other studies also model healthy and sustainable diets with a similar ASF profile [34,37] that roughly corresponds to a halving (-50%) of current meat consumption while maintaining a modest intake of dairy.

Waste reduction

Food loss and waste creates significant adverse environmental and nutritional impacts [174]. 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 [17,37,77,97]. 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 [174,175].

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 modelled 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 [176], 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 [177,178]. Food supply, as reported in the FAOSTAT Food Balance Sheets [172], 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 [104].

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 [17,104] 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 S11).

Table S11. Per capita food supply (kcal person^{-1} day^{-1}) across diet-waste scenario combinations. Waste fractions calculated as weighted averages from data sourced from [17].

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 [179,180] and feature prominently amongst reviewed studies (Table S8). 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 [179]. 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 [109,179,181,182]. 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).

We addressed the compatibility 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 [168,183,184]. 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 [185]. We selected this approach following comparisons with FAOSTAT yield data and discussions with study authors. It also allowed us to include studies [34,106] that assumed aggregate crop yield increases across all crops including cereals, studies [89,156] that assumed cereal yield increases expressed in caloric (kcal ha^{-1}) terms, and all studies [76,107,108,173] that use the MAgPIE model in which yields are calculated endogenously on the basis of a technological change rate [186].

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 [168]. This represents a worst-case-scenario that could also be considered as indicative of potentially negative impacts of climate change on crop yields [47,48,187].
- Trend (30%) – Yields follow a BAU trajectory. Calculations based on data in the reviewed studies (T1 in Data S1) and [184] 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 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 [60,89,99,157]. This also aligns with assumptions under the SSP 1 storyline [112,184] and a 90% yield gap closure for major cereals [179].
- Very high (60%) – Yields increase is highly ambitious at double the BAU trajectory and is representative of optimistic yield gap closure scenarios [17,53,77,184], corresponding to a 100% yield gap closure for most major cereals [179].

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 [168]. 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 [188,189]. 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 [190], and productivity can therefore be measured in several 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 [97,112,133,158].

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 [48,157,191] also significantly impact overall livestock productivity. Pasture productivity can also be a key metric for grass-fed ruminants [89]. Stocking density (i.e., head of stock per unit area) is also used as a relevant metric for livestock fed on pasture [77]. 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 [108]. 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 [17,99,192], but this will not necessarily reduce resource use (i.e., land, water, nutrients) if feed efficiency remains unchanged or feeding levels increase [192]. Similarly, N and P excretion could be reduced by changing feed composition through increasing the use of concentrates or by increasing N conversion rates [157]. 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 [47,76,107,108].

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 [17,53], studies that used a protein conversion ratio[89], and studies where feed efficiency was approximated by an index of livestock productivity [47,114].

Table S12 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 S12), with the Very High setting representing a ~40% reduction in FCRs across livestock categories.

Table S12. 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 [112] to highly efficient but predominantly grassfed dominated systems such as those in Australia and New Zealand [193]. The High setting represents SSP1 scenarios [112]. While some grain-dominated systems [34,171] or dairy systems were meat is a by-product [97] 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 [105].
Dairy	2	1.75	1.5	1.25	The assumed range spans the current global average [194] to that already achieved in efficient but predominantly grassfed systems such as those in Australia and New Zealand or western Europe [158]. Similarly to ruminant meat, highly efficient systems can achieve FCRs closer to 1 (or below) is some cases [112,193], but such FCRs are more representative of grain-dominated systems [171]. The Trend setting represents an average of BAU scenarios across studies assuming mixed production systems [35,37], while the High setting assumes continued intensification as per SSP1 or other moderate efficiency scenarios [34,97,99].
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 [105], in addition to eggs, and aquaculture products in industrial production systems [34,97]. 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 [97,99]. 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 [195]. An increased percentage of calories from aquaculture products consistent with pescatarian or frequently modelled flexitarian diets such as the EAT-Lancet [53], 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 [47,48,97,126,134,196] highlight the potential environmental benefits associated with reducing the proportion of human-edible biomass (e.g., cereal crops) termed *food-competing feed* (FCF) [48] consumed by livestock and increasing the proportion of ecological leftovers (i.e., grass, waste, by-products) or low-opportunity-cost biomass [197] 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 [77]. 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) [107,108]. On the other hand, several studies [47,48,97,157,171,198,199] explicitly modelled scenarios with reduced FCF and higher proportions of grass and by-products as representative of circular economy and agroecology sustainability narratives (Table S7).

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 S12) 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 [47,48,97,106] and those who did not, as several studies [34,37,106] 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 [200] in addition to the classification of residues and by-products as per [47,48], to calculate a base year (2010) FCF percentage across all crops [114]. 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:

$$FCF_r = \frac{\sum_{r=1}^{n} FCF_r * (FCR_r * P_r)}{\sum_{r=1}^{n} FCR_r * P_r} \qquad \text{(Eq. S2)}$$

$$FCF_m = \frac{\sum_{m=1}^{n} FCF_m * (FCR_m * P_m)}{\sum_{m=1}^{n} FCR_m * P_m} \qquad \text{(Eq. S3)}$$

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 S7). To ensure compatibility with BAU trends towards livestock intensification and higher FCRs (Table S12), 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 (Table S13).

Table S13. 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 those in North America [133]. The Trend setting assume intensification following trends consistent with SSP2 scenarios [107,108], while the High and Very High settings are typical of the degree of intensification seen in SSP1 scenarios [112,113]. Some predominantly grass-fed production systems such as in Australia and New Zealand can achieve Very High FCRs at the Low FCR setting [193].
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 [133]. The Trend setting represents an average of BAU scenarios

Livestock category	Low	Trend	High	Very High	Justification
					across studies assuming mixed production systems [37,47,99,107,108], while the High or Very High setting assumes significant intensification as per SSP1 [112], or other high productivity scenarios [97]. 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 [193].
Monogastric	80	85	90	95	The Low setting is representative of production systems with high percentages of residues and fodder typical of developing countries [194], or more circular systems [97]. The Trend and High settings assume further global intensification and increases in FCFs consistent with BAU/SSP2 [107,108] and high productivity/SSP1 [97] trends respectively. The Very High setting assumes almost 100% crop-based feed as seen in highly productive industrialised systems [97,106]. 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 (GHG emissions intensity and carbon price)

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 [78,201-203], in addition to CO_2 savings related to energy and transport in the food supply chain both upstream and downstream [84,106,204], and concerted global efforts to eliminate cropland and pasture expansion and maximize land-based GHG sequestration [205-207]. 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 [75,79,83], 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 [192,208], improved manure management and infrastructure [209], 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 [201,204].

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 [83]. Several of the reviewed studies [76,100,112,210] 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) [201,204]. However, most studies did not directly incorporate a carbon price, with some modelling ecosystem conservation and restoration efforts such as payments for ecosystem services (e.g., REDD) [76,99,100,112]. Many studies and scenarios assumed either constant GHG intensities into the future e.g., [47,89,183], or considered potential GHG intensity reductions based on either past trends [90,106] or mitigation potentials from the literature associated with technological advances or improved management [17,34,97,99]. While most studies assumed simultaneous (but often different) intensity reductions for both CH_4 and N_2O, a few studies [35,37,171] 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 [29]. Where CH_4 and N_2O emissions intensity was not explicitly provided in the study supplementary data [17,34,53], 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 [192], 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 [76,112] 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 [76,112].

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_2eq^{-1}) – GHG intensities remain constant at base year levels assuming no changes in technology or farming practices e.g., [47,89,183], and there are no active efforts to curtail LUC emissions.
- Trend (13/4%, 25 \$ t CO_2eq^{-1}) – 13/4% reduction in in CH_4/N_2O intensities represents an average mid-point for BAU scenarios from [90,106,211]. The carbon price corresponds to a BAU mitigation effort in terms of LUC emissions that corresponds to SSP2 [76,112].
- High (26/8%, 100 \$ t CO_2eq^{-1}) – 26/8% reduction in CH_4/N_2O intensities represents an ambitious improvement well above past efficiency trends [106]. This percentage is also consistent with a high mitigation scenario for livestock in [114,208] 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 [76,79,99].
- Very high (40/12%, 200 \$ t CO_2eq^{-1}) – At around two to three times the rate estimated from the highest BAU trend [106] and comparable to the highest assumed intensity reductions assumes across studies for CH_4 [34,99,112], 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 [83,201,204,212]. 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 [79,83].

Water-use efficiency

As the main sector of water, accounting for ~71% of global freshwater withdrawals in 2020 [213], and given the anticipated increase in food demand, agriculture will continue to exerts significant pressure on water-related environmental limits [14,16,54]. 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 [214]. 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 [215].

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 [216,217]. 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* [109,215], is the ratio of crop yield (or biophysical crop production) to the volume of water consumed ('crop per drop') [215]. This definition, which also corresponds to the inverse of the blue water footprint [218] 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) [219]. 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 [168,215,220], with several reviewed studies reporting this metric. Some studies [106,112] 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) [221].

We selected water productivity (i.e., ratio of crop yield to the volume of water withdrawals) as our default WUE metric. While most reviewed studies [68,108,109,222] 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 harmonize our selected WUE metric 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 withdrawals due to high variability in regional WUEs across agricultural sectors [223]. 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 to simulate total water withdrawals assuming base year productivities for each future scenario (see Eq. S4). To further harmonize across studies, we then compared the simulated water withdrawal estimate to the actual water withdrawals of each scenario to compute the percentage change in WUE relative to the base year for each future scenario, as per Eq. S5.

$$SWW_s = \sum_{c=1}^{n} \frac{BWW_{bc}}{P_{bc}} * P_{sc} \quad \text{(Eq. S4)}$$

$$WUE_s = [1 - (AWW_s - SWW_s)] * 100 \quad \text{(Eq. S5)}$$

where SWW stands for static water withdrawals (assuming base year water footprints), BWW is global blue water withdrawals by commodity (in m^3), P is the global commodity production (in tons), and AWW is the actual water withdrawal 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 GHG intensity, i.e. by comparing total (as opposed to commodity-specific) blue water withdrawals 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 2005-2010 range which ensured consistency given that it is broadly accepted that improvements in WUE at the global level were limited during this period [168]. While virtual water trade [224] is not explicitly modeled as an intervention (see 1.4.3), the assumed intervention levels could be considered to incorporate the water-saving potential of concentrating production to more water-efficient locations [223,225]. In some scenarios [170] 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 [61,108,109,222]. For two of the studies [109,222], 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 [47,48,156,170] into the future.

- Trend (5%) – We took the efficiency increase estimate from [69,109] 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 [222].
- High (10%) – WUE increases at twice the BAU rate. This level of increase corresponds to that assumed in SSP1 scenarios [68,112].
- Very high (15%) – This rate of increase is three times the BAU rate and corresponds to a highly optimistic global effort to improve WUE in agriculture. This values if just below the ~20% increase assumed in the most optimistic scenarios [68,108].

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 [102,226]. 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 [113]. 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 [102,217,226].

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) [227]. 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 [168,228]. Other indicators such as soil N uptake efficiency [173,229] and fertilizer efficiency gain [162,230] 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 [37,226,228]. Hence, we included NUE_N and NUE_P as two distinct predictor variables in the N_{fert} and P_{fert} 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 [37,226,228]. In two cases where this metric could not be calculated due to a lack of available data [77,106], 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 [227], 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 [106,161], or assumed current application rates and use intensities [47,48,114].
- Trend (10/5%) – NUE_N / NUE_P increases at an average historical rate assumed across a range of BAU scenarios in reviewed studies [111,173,198,228,231].
- 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 [17,37,53,111] and is identical for NUE_P but only slightly above the 15% assumed for NUE_N in SSP1 scenarios in [113].
- Very high (30/15%) – NUE_N / NUE_P increases substantially. For NUE_N, this level is compatible with the ‘Tech+’ scenario in [17,53,157] and Technogarden in [157], as well as the combined mitigation scenario in [35], but is slightly lower than the sustainable pathway target (38% assuming a baseline NUE_N of 0.46) in [217] for $NUE_{N.}$ Only two studies [173,231] 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 [102,232]. For NUE_P this corresponds to the most efficient scenarios in [37,111].

Nutrient recycling

The recycling of nitrogen and phosphorus, similarly to NUE, has the potential to reduce overall demand and application of chemical N and mined P [17,37,111,228]. Reducing losses and increasing phosphorus recycling are seen as key to achieving a more closed-loop anthropogenic phosphorus system [226,233]. While recycling of N or P within the agricultural system (e.g., from animal manure in grasslands or crop residues) is common in many agricultural systems, any recycled N/P from sources outside this system, such as from imported manure, waste, and human excreta, could further offset requirements for fertilizer. For example, the recycling of human waste for the purposes of rice cultivation has been practiced for centuries in Asia [157]. The extent to which this N/P source is likely to have a significant global impact in reducing N/P fertilizer use and surplus in agriculture has been debated [233]. However, we considered this the role of nutrient recycling more broadly to have sufficient technical and feasibility potential to warrant consideration.

Variants of this intervention are modelled in selected scenarios [35,37,111,113,173,231] and are accompanied by percentages of increased nutrient recycling. Older scenario narratives such as the Millennium Assessment scenarios [157,228] also provide information that suggests that some of the N or P comes from recycled sources but these were not used in the analysis due to having older base years and modelling assumptions. To ensure that the results of the statistical models remain unbiased to assumptions around recycling, we excluded scenarios that assumed offsets in N or P fertilizer due to recycled N from outside the agricultural system. To simulate the potential of recycling scenarios, we then carried out a simple linear adjustment on the final calculated fertilizer demand for each scenario, as in [17].

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 [229], or whether the storyline dictates that all manure must be recycled [111,231], 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 [157,228]. However, this metric could not be adequately harmonized across studies and was therefore not subsequently used.

In terms of intervention strategies, we focus here on the potential use of recycled N/P from all sources (agricultural and human sources) to offset chemical or mined N/P. We established the following percentage levels of reductions in N/P fertilizer due to recycled nutrient inputs based on the reviewed literature (N%, P%):

- Low (0/0%) – This is consistent with most scenarios that assume no additional recycling of household waste and human excreta relative to the current situation. This setting is also applicable to all studies where nutrient recycling is not explicitly modelled as an intervention.
- Trend (10/15%) – This is compatible with increased recycling of household waste and sewage as seen in SSP2 scenarios [113,173].
- High (20/30%) – This setting is midway between the percentage offset in fertilizer deemed possible in [37] and the ambitious Tech+ scenario in [17,53] which originates from [233].

- Very high (30/45%) – For N, this is slightly more ambitious that the assumption that a 100% recycling of human excreta could offset ~25% of N fertilizer[37]. For P, this percentage is just below the 50% recycling rate assumed in the Tech+ scenario in [17,53].

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 [47,114,171,196]. Only 1.4% of current total global farmland is under organic production [234]. 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 [60,181]. From an environmental limits' 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 [47,196].

Some studies have modelled scenarios that include different contributions from organic agriculture to the overall food production system [47,114,196]. The extent of organic production is typically defined as the percentage of area or food production under organic agriculture [47]. To control for this intervention we specifically excluded scenarios that featured organic agriculture [47,114] in N/P fertilizer and N_2O meta-regression models.

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 [174,182,223]. 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 [61,69,112,235]. 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 [198]. 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 [89,117], other studies only define the overall trade regime in qualitative terms (e.g., regional or self-sufficient versus more globalized or open) as dictated by their underlying scenario narratives.

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 [89] 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 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 (see 1.4.2). While significant efficiency gains achieved through these conventional means reflect changes to current practices that can be transformational in nature (e.g., new highly productive crop breeds, technological innovation in water resource management), they can be considered to fall under *sustainable intensification* [236-238], and are readily quantified by assumptions of future changes in the metrics already described (see 1.4.2, 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 [129]; significant global transition to aquaculture-sourced protein [97]; or alternative animal feed supply routes such as those based on industrial production of microbial proteins [125,131]. 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 [129]. Recent modeling studies have modelled some disruptive or breakthrough technologies. These include artificial meat [97] or technologies and feed supplements that can significantly reduce methane emissions in ruminant livestock or capture carbon emissions [99]. 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 [97,99] from all statistical models as their effect on resource use indicators was partly controlled for by Crop yields, GHG intensity, FCRs, and feed composition.

1.4.4 Model fitting and selection

LMMs for environmental indicators other than CO2 from land-use change

An LMM that follows the standard form of the random intercept model in matrix notation, as proposed in [239] was fitted for each indicator (see Table S2), as follows:

$$y_{j,s} = X_{j,s}\beta_j + Z_{j,s}b_{j,s} + \varepsilon_{j,s} \qquad \text{(Eq. S7)}$$

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 [240]. 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 [3] who used percentage change relative to the base year as the response variable. All LMMs were fitted using the R package *lme4* [241].

We used either a random intercept only or 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 [145,242,243]. We made an exception in the case of water, methane, nitrous oxide where we also allowed a random slope for the yield fixed effects to control for significant differences in the dynamics of models. 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 [146], 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 [244]. For example, where studies used the same model but report results for different scenarios [17,53], 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 [245]. While a more maximal random effect structure [246] with two random intercepts, one at the study and another at the model level, was used in a recent study [3], this reduced model fits in our case, while resulting in over-parameterized models and loss of power given available sample sizes, as argued in [247]. 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. However, 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 (or models) with fewer scenarios [145,245].

Modelling CO_2 associated with land-use change

Agriculture emissions from land use and land-use change activities are highly uncertain [84,248], with studies often adopting different assumptions with respect to the biophysical processes and emission sources included [46,82]. This is also the case for the studies in our database as determined following an audit of all 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 the GHG emissions environmental limits (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 (Data S1), which were nevertheless compiled for completeness, with notes indicating the processes included or excluded.

Similarly to [34], 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 [77,110]. 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 [110].

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 [34]. While this approach produced figures of annual CO_2 LUC emissions comparable to the literature [34] when coupled with our cropland predictions, it did not account for emissions associated with pasture expansion [77] 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 sample of 2,232 CO_2 LUC estimates spanning the period 2010-2050 representing all land use models runs used in IPCC AR6 [82,83] available in the Integrated Assessment Modeling Consortium (IAMC) AR6 Scenario Database [29] 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 which also includes any afforestation following agricultural abandonment/expansion) as the dependent variable, and annual change in cropland (*delta cropland*), pasture (*delta pasture*), carbon price, and year as fixed effect predictors. Following preliminary data exploration, we restricted the training sample to scenarios from the following IAMs because of their explicit endogenous representation of AFOLU measures including land use change and their compatible cropland and pasture values [82]: IMAGE 3.0/3.0.1/3.02/3.2, GCAM-PR 5.3, MESSAGE-GLOBIOM 1.0, MESSAGEix-GLOBIOM 1.0/1.1/1.2/GEI 1.0, REMIND-MAgPIE 1.5/1.7-3.0/2.0-4.1/2.1-4.2/2.1/4.3, WITCH-GLOBIOM 3.1/4.2. Following additional exploration of each fixed effect predictor against the grouping variable (model), we only used observations from the following models: IMAGE 3.0/3.0.1/3.2, MESSAGEix-GLOBIOM 1.1/1.2, REMIND-MAgPIE 2.1/4.3 as they match the models for which non-CO_2 emissions were available, and they also display similar responses to changes in cropland and pasture over time.

Following the example of [146], 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 1.4.4 (see also Table S14 for cross-validation statistics and Table S21 for 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 4.3 BAU projection of ~3.75 Gt CO_2e [115,121] while the upper estimate (mean + 2*SD) is comparable to the IMAGE 3.2 estimate of ~6 Gt CO_2e [115].

A number of important assumptions and caveats need to be acknowledged. As per [34], 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 [77,110]. 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 [82].

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 1.5.1) in order to emulate as closely as possible the original process-based models and 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 [249,250]. 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* [251] and *car* [252]. 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 [3], 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) [253].

b. We considered alternative fixed and random (in the case of blue water and N_2O) effect structures whereby fixed effects were derived as 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 [142]. This included testing the addition of an initial condition delta relative to 2010 base year values (see Table S24) following [103]. 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* [254] 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 [255]. Predictors with a VIF > 5 were considered as potentially problematic [145]. 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* [256]. 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* [241]. 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 [145,240]. 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 [257], following the example of [258]. Recent work highlights that LMMs are often robust to such violations [259].

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* [260] to better match coefficients in the LMM to those in the robust version, as per [261]. 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 [262] and calculated using the R package *MuMIn* [263]. Model performance metrics of the final selected models are presented in Table S14. Full global model summaries, produced using the R package *sjPlot* [264], are presented in 1.5.3.

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* [147] 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 S14. Model performance metrics following repeat cross-validation with for selected meta-regression models implemented in the R package *cvms* [254]. [RMSE = root mean square error, NRMSE = normalised root mean square = RMSE / range, 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	NRMSE	AIC	AICc	R^2m	R^2c	Effect size metric
Cropland	Process-based	0.16	0.20	-2004.28	-2004.12	0.70	0.93	LnR
Pasture	Process-based	0.19	0.25	-283.091	-282.912	0.69	0.79	% change
CH_4	Process-based	0.07	0.10	-771.297	-770.187	0.93	0.97	LnR
N_2O	Process-based	0.13	0.23	-678.099	-676.676	0.70	0.96	LnR
CO_2 LUC	Process-based	1710	0.21	27435.34	27435.4	0.70	0.83	Mt CO_2e yr^{-1}
Water	Process-based	0.11	0.23	-776.019	-775.044	0.74	0.94	LnR
N_{fert}	Process-based	0.18	0.27	-1212.07	-1211.7	0.71	0.92	LnR
P_{fert}	Process-based	0.12	0.24	-643.839	-642.688	0.64	0.81	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 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:

$$ER_{j,l} = P(Y_{j,l} > X_j) \qquad \text{(Eq. S8)}$$

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 1.4.4). X_j is a random draw from the probability density function representing the uncertainty in environmental limits (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* [256] and *extraDistr* [265]. Fig. S3 illustrates the *ER* calculation for the agricultural area limit in the case where all interventions are set to their Trend level (see Table S24 for Trend level prediction estimates).

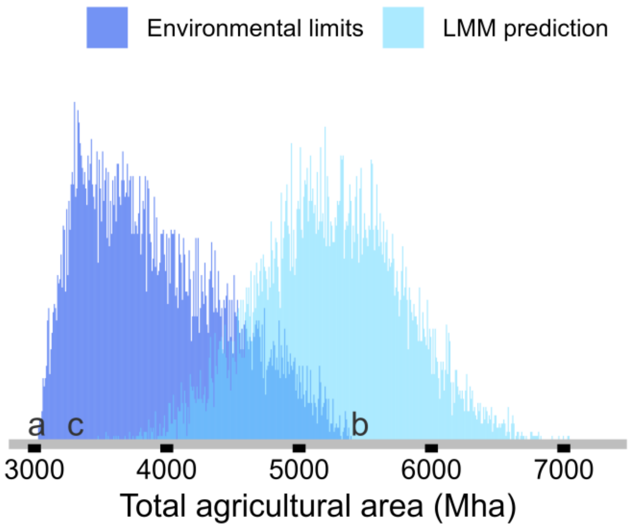


Fig. S3. Illustrative example of the *ER* calculation method to account for uncertainty in LMM predictions and environmental limits. ER for agricultural area is calculated as the probability of a random value from the normal distribution of prediction estimates (Mean = 5224 Mha, SD = 561 Mha) exceeding a random value from the triangular distribution of the environmental limits (a = 3019 Mha, b = 3309 Mha, c = 5460 Mha), based on 10,000 random draws from each respective distribution. *ER* = 0.95 in this case (see Table S24).

1.4.6 Identifying risk-compliant intervention 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 environmental limit into an integrated dataset by 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 1,048,576 plausible intervention level combinations across all boundaries (Table S15). The Pareto plot in Fig. S5 illustrates the trade-off between intervention level (calculated as the average ambition level across all relevant interventions) and exceedance risk (calculated as per Fig. S3).

Table S15. Modelled interventions and total intervention-level combinations for each environmental limit and combined for all limits.

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	$4^8 = 65{,}536$	+ GHG intensity
Freshwater use	8	$4^8 = 65{,}536$	+ WUE
Biogeochemical flows	8	$4^8 = 65{,}536$	+ N & P management. Both were allowed to vary independently of each other to create two pooled risk datasets for N & P respectively.
Integrated dataset	11	1,048,576	The four individual environmental limit 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 combinations.

Using the integrated dataset with all intervention-level combinations across all environmental limits, we filtered scenarios that met two critical IPCC-calibrated uncertainty risk thresholds [151] 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. This was done individually for each environmental limit (see Fig. S6 for agricultural area, Fig. S7 for GHG emissions, Fig. S8 for surface water flows, Fig. S9 for nutrient cycles) and then combined for all environmental limits (see main paper for results).

1.5 Note S5 - Statistical model variables and summaries

1.5.1 Model parameterization and variable selection

As previously described (see 1.4.4), for each indicator we tested alternative fixed effects structures that incorporate the process-based logic used in the original models with aggregates of variables used as independent predictors and selected the best ones on the basis of their superior inference (process-based logic that captures key biophysical processes) and superior prediction skill (i.e., the lowest RMSE cross-validation score). The following sub-sections summarize the parameterization logic behind the choice of composite variables (see 1.5.2) used in each statistical model.

Agricultural area

We assumed that cropland extent is determined by the total demand (consumption + waste) for food crops (see Eq. S9) in addition to crop feed requirements for monogastric and ruminant livestock products [110]. 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 feed demand. We excluded studies where cropland was not an explicit output of the modelling, studies with limited crop coverage, and scenarios that assumed no feed contribution from pasture (Table S5).

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, studies with low base year pasture estimates, and studies and scenarios that kept pasture area constant (Table S5).

Water withdrawals

We assumed that blue water withdrawals are 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 [266]. 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 [108]. Total plant calories (Eq. S9) and WUE (defined as the ratio of yield relative to the volume of water consumed, see 1.4.2) were also added as fixed effects predictors. We allowed a random slope for the WUE fixed effects predictor to control for the heterogeneity in responses to increase WUE that exists between the underlying models (see 1.4.4). We excluded studies that only provided estimates for water consumption, had limited crop coverage, or did not explicitly model the relationship between crop yields and water demand (Table S5).

Greenhouse gas emissions

To model CH_4, we defined composite predictors to cover the three key sources: enteric fermentation, manure management, and rice cultivation (see 1.3.7). We assumed that ruminant meat acts as the key determinant of enteric fermentation, with enteric fermentation from non-ruminant animals known to be very modest in comparison [267]. To capture CH_4 associated with both enteric fermentation and manure management we specified composite predictors that account for the total amount of feed in ruminant meat (Eq. S22) and non-ruminant and dairy animals (Eq. S24) as a determinant of total manure production, controlling also for livestock productivity (assumed to follow the trend in feed efficiency), which in turn determines livestock numbers and feed demand [192]. Total plant calories (Eq. S9) were used as a proxy for rice demand as rice paddies are an important source of methane emissions [99]. 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 [192]. We excluded studies that did not provide a breakdown of non-CO_2 emissions or has a limited emissions scope as indicated by their lower base year values (Table S5).

To model N_2O, we defined composite predictors to cover the following key sources: agricultural soils (synthetic fertilizer and manure left on pasture are the dominant sources) and manure management from confined animal operations (see 1.3.7). We assumed that both crop (Eq. S17) and grass feed (Eq. S20) require nutrient fertilization but assigned separate predictors in each case to account for the differences in N_2O emission processes associated with cropland and pasture [268]. 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 [269]. We also assumed that manure production is proportional to total feed intake [267]. 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 1.4.4). Total plant calories (Eq. S9) and a N_2O intensity (calculated as a weighted average across all CH_4 emission components, as detailed in 1.4.2) we also added as fixed effects predictors. We excluded studies for which the upstream CO_2 emissions associated with fertilizer production could not be separated, and studies with unresolved issues around the breakdown of N_2O emissions into different sources or which has a limited N_2O emissions scope (Table S5).

For parameterization of the CO_2 LUC model, see 1.4.4.

Nutrient cycles

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 [227] who reported that <5% of fertilizer nitrogen is applied to grassland. In both models 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 a fixed effects predictors to control for the level of nutrient-use efficiency (NUE_N / NUE_P) following the approach detailed in 1.4.2. Studies with very few numbers of scenarios, those that lacked consistent NUE and yield metrics, and scenarios with organic agriculture or recycling offsets were all excluded (Table S5).

1.5.2 Composite variables used as predictors

The following equations describe the calculation of the composite variables used as fixed effects predictors. See 1.5.3 for model summaries.

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

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

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

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

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

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

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

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

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

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

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

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

$$OtherFeed_m = TotalSupply_m * FCR_m * (1 - FCF_m) \quad \text{(Eq. S21)}$$

$$AllFeed_r = GrassFeed_r + CropFeed_r \quad \text{(Eq. S22)}$$

$$AllFeed_d = GrassFeed_d + CropFeed_d \quad \text{(Eq. S23)}$$

$$AllFeed_{rd} = AllFeed_{rd} + AllFeed_{rd} \quad \text{(Eq. S24)}$$

$$AllFeed_m = CropFeed_m + OtherFeed_m \quad \text{(Eq. S25)}$$

$$AllFeed_{dm} = CropFeed_d + GrassFeed_d + AllFeed_m \quad \text{(Eq. S26)}$$

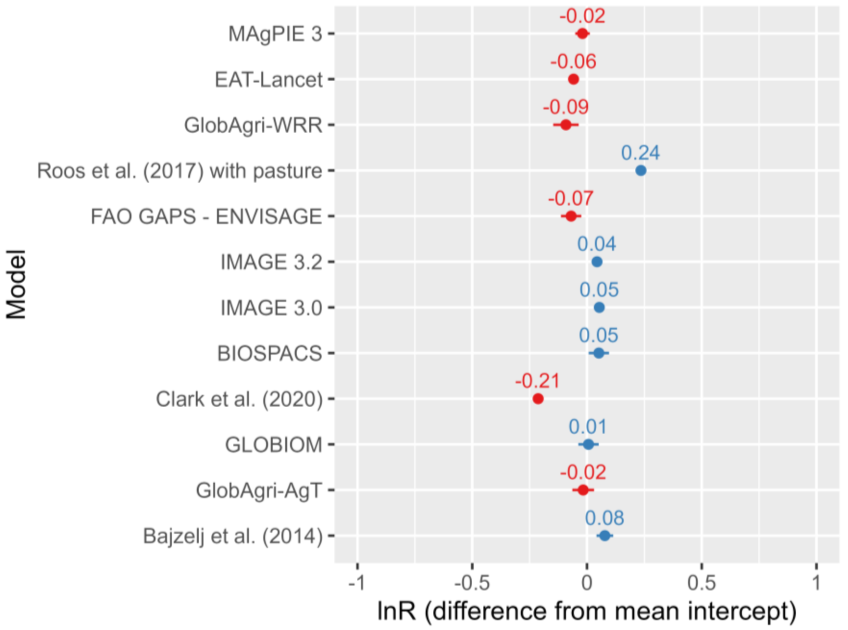
where *r* are ruminant meats (beef, mutton and goat), *d* is dairy (milk excluding butter), *m* are monogastric products (chicken, pork, eggs, and aquaculture), *p* are all crops directly consumed by humans, *FCR* is the feed conversion ratio, and *FCF* is the ratio of feed from crops in direct competition with food. *rd* is used when referring to combined totals for all ruminant animals while *rdm* is used when referring to combined totals for all ruminant and monogastric 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 [105] to ensure compatibility with FCR units. $OtherFeed_m$ refers to non-FCF residues and by-products as per [47,48].

1.5.3 Statistical model summaries

Below we present the model summaries of each of the LMMs fitted using the R package *lme4* [241] along with robust LMM versions fitted using the R package *robustlmm* [257] 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 1.5.2). %Δ denotes change relative to the base year value. All tables were produced with the R package *sjPlot* [270].

Table S16. Cropland (LnR) model summary.

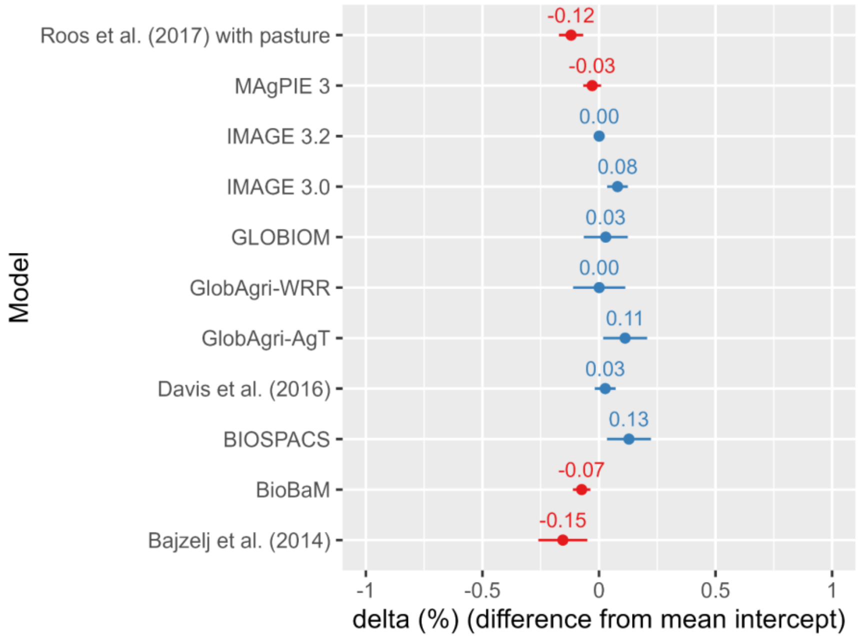
	Cropland (LMM)			Cropland (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.03	-0.10 – 0.04	0.407	-0.03	-0.09 – 0.03	0.327
$\text{CropFeed}_{\text{rdm}}$ (%Δ)	0.08	0.08 – 0.09	**<0.001**	0.09	0.08 – 0.09	**<0.001**
$\text{TotalSupply}_{\text{p}}$ (%Δ)	0.09	0.08 – 0.09	**<0.001**	0.09	0.08 – 0.09	**<0.001**
Crop yields (%Δ)	-0.20	-0.20 – -0.19	**<0.001**	-0.20	-0.20 – -0.19	**<0.001**
Initial condition delta	0.01	-0.02 – 0.04	0.483	0.00	-0.02 – 0.03	0.844
Random Effects						
σ2			0.00			0.00
τ00			0.01 Model			0.01 Model
ICC			0.76			0.72
N			12 Model			12 Model



Observations			955			972
Marginal R^2 / Conditional R^2			0.706 / 0.929			0.770 / 0.936
AIC			-2396.908			
AICc			-2396.790			

Table S17. Pasture (delta %) model summary.

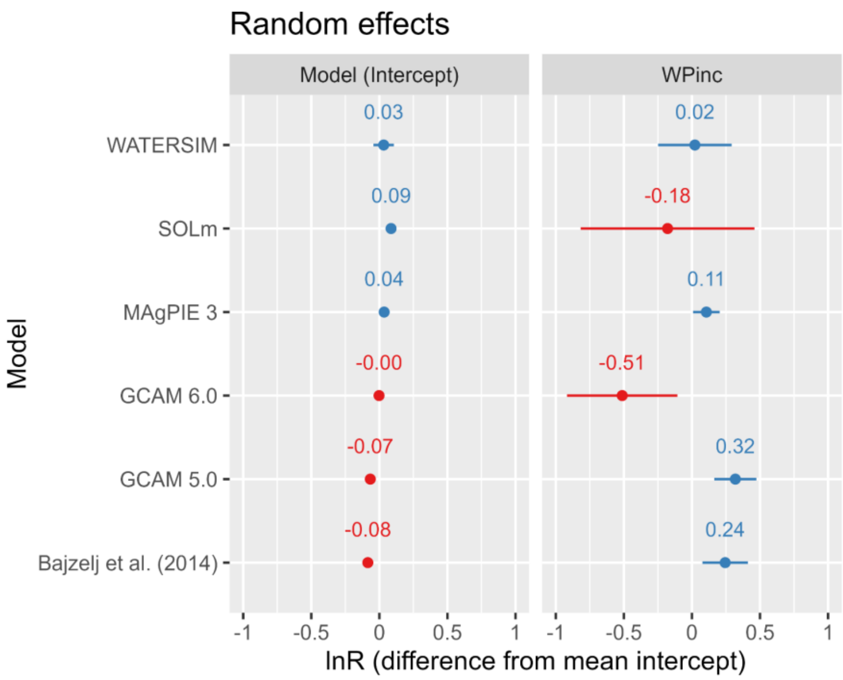
	Pasture (LMM)			Pasture (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.11	-0.17 – -0.04	**0.002**	-0.10	-0.18 – -0.02	**0.010**
$GrassFeed_{rd}$ (%Δ)	0.30	0.28 – 0.31	**<0.001**	0.30	0.28 – 0.31	**<0.001**
Initial condition delta	-0.01	-0.07 – 0.04	0.613	-0.02	-0.07 – 0.04	0.533
Random Effects						
σ^2			0.02			0.02
τ_{00}			0.01 Model			0.01 Model
ICC			0.30			0.42
N			11 Model			11 Model



Observations			434			438
Marginal R^2 / Conditional R^2			0.713 / 0.799			0.723 / 0.840
AIC			-336.357			
AICc			-336.217			

Table S18. Blue water withdrawals (LnR) model summary. WPinc = WUE (%Δ) = increase in water use efficiency (%).

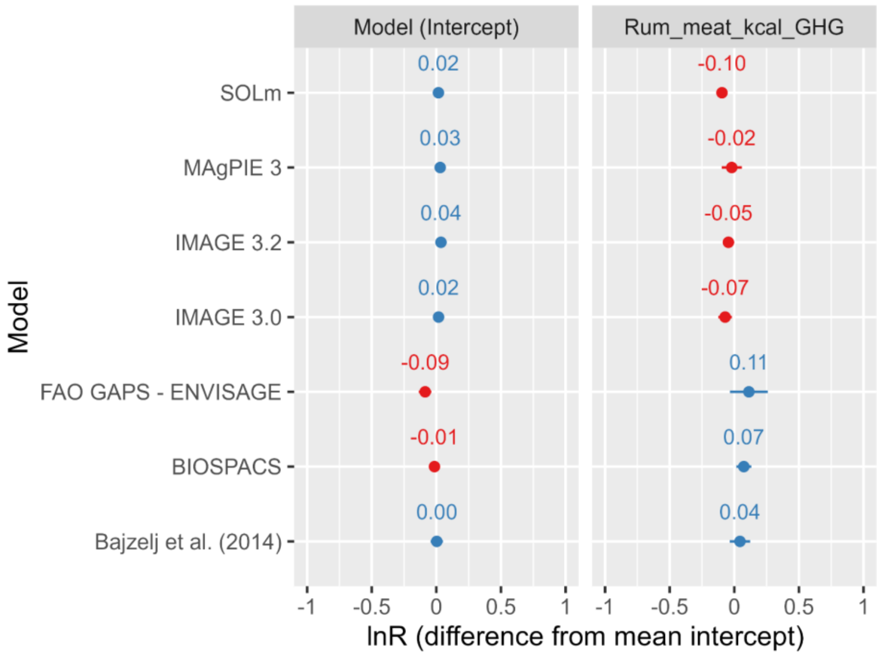
	Blue water (LMM)			Blue water (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.16	0.10 – 0.22	<0.001	0.16	0.11 – 0.22	<0.001
$CropFeed_{rdm}$ (%Δ)	0.10	0.09 – 0.10	<0.001	0.10	0.09 – 0.10	<0.001
$TotalSupply_{p}$ (%Δ)	0.07	0.06 – 0.08	<0.001	0.07	0.06 – 0.07	<0.001
Crop yields (%Δ)	0.00	-0.00 – 0.01	0.374	0.00	-0.00 – 0.01	0.308
WUE (%Δ)	-0.12	-0.15 – -0.08	<0.001	-0.12	-0.16 – -0.08	<0.001
Initial condition delta	0.02	-0.04 – 0.08	0.460	0.02	-0.04 – 0.08	0.472
Random Effects						
σ^2			0.00			0.00
τ_{00}			0.01_{Model}			0.01_{Model}
τ_{11}			$0.13_{\text{Model.WPinc}}$			$0.20_{\text{Model.WPinc}}$
ρ_{01}			-0.43_{Model}			-0.49_{Model}
ICC			0.75			0.77
N			6_{Model}			6_{Model}



	Blue water (LMM)	Blue water (robust LMM)
Observations	309	310
Marginal R^2 / Conditional R^2	0.768 / 0.942	0.783 / 0.950
AIC	-971.771	
AICc	-971.033	

Table S19. Methane (LnR) model summary.

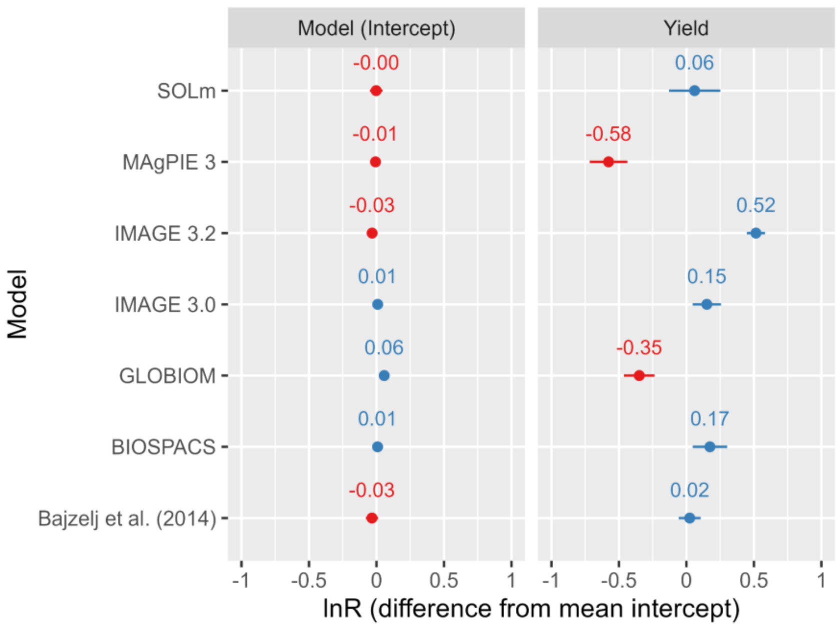
	CH_4 (LMM)			CH_4 (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.07	0.04 – 0.10	**<0.001**	0.07	0.04 – 0.10	**<0.001**
$AllFeed_r$ (%Δ)	0.14	0.12 – 0.16	**<0.001**	0.15	0.12 – 0.17	**<0.001**
$AllFeed_{dm}$ (%Δ)	0.01	-0.00 – 0.03	0.124	0.01	-0.01 – 0.03	0.217
$TotalSupply_p$ (%Δ)	0.02	0.01 – 0.03	**<0.001**	0.02	0.01 – 0.03	**<0.001**
CH_4-intensity (%Δ)	-0.12	-0.12 – -0.11	**<0.001**	-0.12	-0.12 – -0.11	**<0.001**
Initial condition delta	0.04	0.02 – 0.05	**<0.001**	0.03	0.02 – 0.05	**<0.001**
Random Effects						
σ^2			0.00			0.00
τ_{00}			0.00 Model			0.00 Model
τ_{11}			0.01 Model.Rum_meat_kcal_GHG			0.01 Model.Rum_meat_kcal_GHG
ρ_{01}			-0.77 Model			-0.63 Model
ICC			0.59			0.50
N			7 Model			7 Model



	CH_4 (LMM)	CH_4 (robust LMM)
Observations	307	313
Marginal R2 / Conditional R2	0.922 / 0.968	0.934 / 0.967
AIC	-1022.863	
AICc	-1022.120	

Table S20. Nitrous oxide (LnR) model summary.

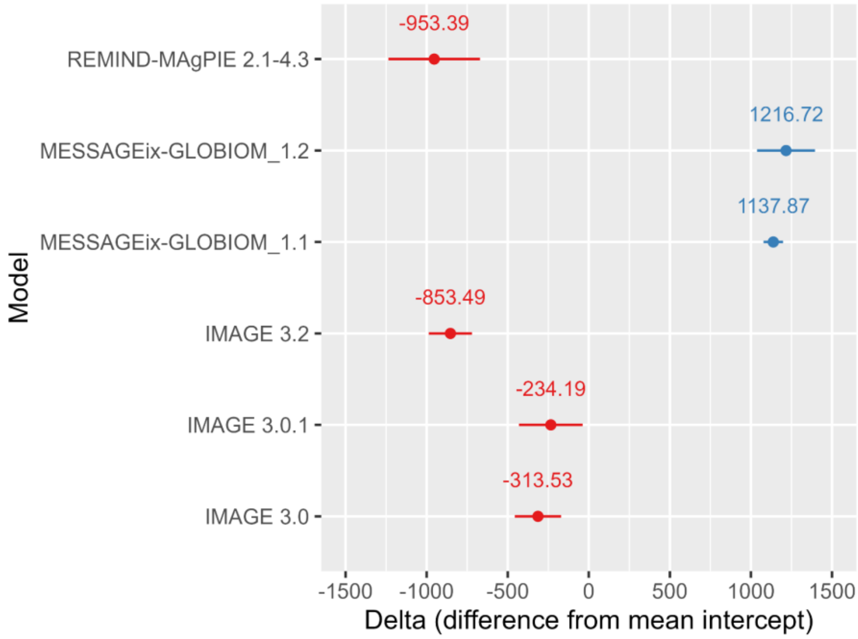
	N_2O (LMM)			N_2O (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.15	0.07 – 0.23	**<0.001**	0.15	0.07 – 0.24	**<0.001**
$GrassFeed_{rd}$ (%Δ)	0.06	0.05 – 0.07	**<0.001**	0.05	0.04 – 0.07	**<0.001**
$CropFeed_{rdm}$ (%Δ)	0.07	0.06 – 0.08	**<0.001**	0.08	0.07 – 0.09	**<0.001**
$TotalSupply_{p}$ (%Δ)	0.03	0.02 – 0.04	**<0.001**	0.03	0.02 – 0.04	**<0.001**
Crop yields (%Δ)	0.01	-0.02 – 0.05	0.421	0.01	-0.02 – 0.05	0.521
N_2O-intensity (%Δ)	-0.10	-0.11 – -0.10	**<0.001**	-0.10	-0.11 – -0.10	**<0.001**
Delta initial	0.03	0.01 – 0.04	**0.002**	0.02	0.00 – 0.04	**0.032**
Random Effects						
σ^2			0.00			0.00
τ_{00}			0.00 $_{Model}$			0.00 $_{Model}$
τ_{11}			0.13 $_{Model.Yield}$			0.14 $_{Model.Yield}$
ρ_{01}			-0.42 $_{Model}$			-0.35 $_{Model}$
ICC			0.47			0.65
N			7 $_{Model}$			7 $_{Model}$



Observations	264	269
Marginal R2 / Conditional R2	0.909 / 0.952	0.899 / 0.965
AIC	-819.777	
AICc	-818.729	

Table S21. CO_2 LUC (Mt CO_2e yr^{-1}) model summary.

	CO₂ LUC (LMM)			CO₂ LUC (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	1805.64	1032.54 – 2578.73	**<0.001**	1812.12	880.94 – 2743.30	**<0.001**
Delta cropland	567.27	505.12 – 629.42	**<0.001**	580.52	514.78 – 646.27	**<0.001**
Delta pasture	923.21	860.20 – 986.21	**<0.001**	901.05	834.64 – 967.45	**<0.001**
Carbon price	-163.02	-217.50 – -108.54	**<0.001**	-187.78	-245.29 – -130.26	**<0.001**
Year	-1500.15	-1555.41 – -1444.9	**<0.001**	-1531.78	-1589.98 – -1473.6	**<0.001**
Random Effects						
σ^2			1276444.71			1385841.75
τ_{00}			922253.78 $_{\text{Model}}$			1276795.23 $_{\text{Model}}$
ICC			0.42			0.48
N			6 $_{\text{Model}}$			6 $_{\text{Model}}$



Observations			2203			2232
Marginal R2 / Conditional R2			0.716 / 0.835			0.677 / 0.832
AIC			37216.644			
AICc			37216.695			

Table S22. N_{fert} (LnR) model summary.

	N_{fert} (LMM)			N_{fert} (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.09	0.00 – 0.17	**0.047**	0.08	0.02 – 0.14	**0.015**
$CropFeed_{rdm}$ (%Δ)	0.09	0.08 – 0.10	**<0.001**	0.09	0.08 – 0.10	**<0.001**
$TotalSupply_p$ (%Δ)	0.10	0.09 – 0.10	**<0.001**	0.10	0.09 – 0.10	**<0.001**
Crop yields (%Δ)	0.03	0.02 – 0.04	**<0.001**	0.03	0.02 – 0.04	**<0.001**
NUE_N (%Δ)	-0.16	-0.17 – -0.16	**<0.001**	-0.17	-0.18 – -0.16	**<0.001**
Initial condition delta	-0.04	-0.11 – 0.02	0.177	-0.04	-0.09 – 0.01	0.098
Random Effects						
σ^2			0.01			0.01
τ_{00}			0.01 Model			0.01 Model
ICC			0.66			0.47
N			7 Model			7 Model
Observations			743			756
Marginal R^2 / Conditional R^2			0.760 / 0.918			0.806 / 0.896
AIC			-1582.701			
AICc			-1582.505			

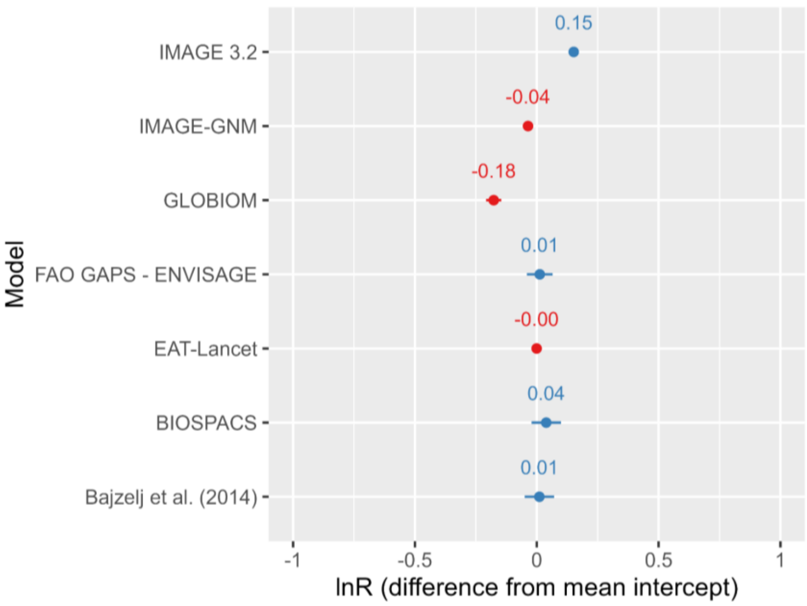
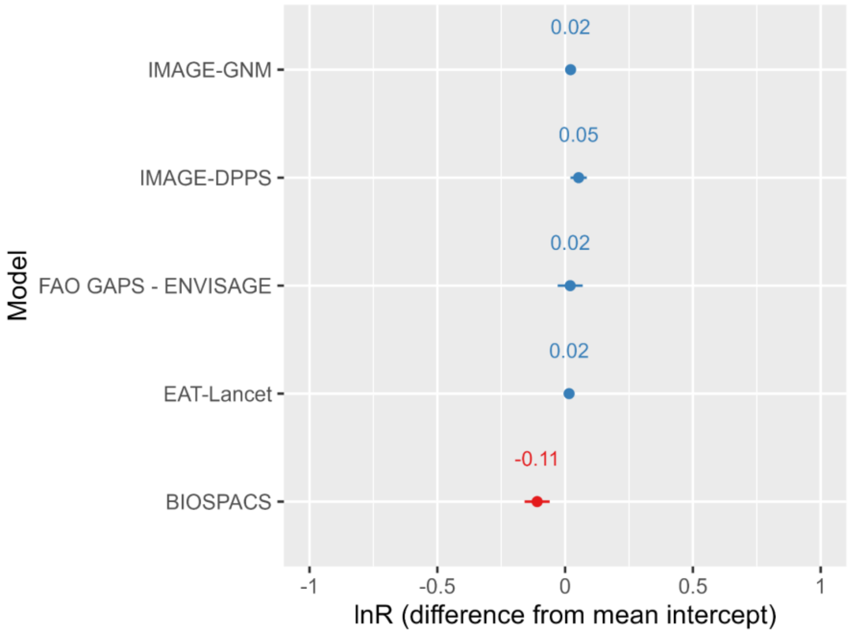


Table S23. Pfert (LnR) model summary.

	Pfert (LMM)			Pfert (robust LMM)		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.16	0.09 – 0.23	**<0.001**	0.16	0.09 – 0.23	**<0.001**
$CropFeed_{rdm}$ (%Δ)	0.08	0.07 – 0.09	**<0.001**	0.08	0.07 – 0.09	**<0.001**
$TotalSupply_{p}$ (%Δ)	0.09	0.08 – 0.10	**<0.001**	0.09	0.09 – 0.10	**<0.001**
Crop yields (%Δ)	0.03	0.01 – 0.04	**<0.001**	0.03	0.01 – 0.04	**0.002**
NUE_{P} (%Δ)	-0.04	-0.06 – -0.03	**<0.001**	-0.04	-0.06 – -0.03	**<0.001**
Initial condition delta	0.01	-0.04 – 0.06	0.758	0.01	-0.04 – 0.05	0.803
Random Effects						
σ^2			0.01			0.01
τ_{00}			0.01 Model			0.01 Model
ICC			0.51			0.47
N			5 Model			5 Model



Observations	421	421
Marginal R2 / Conditional R2	0.612 / 0.808	0.615 / 0.796
AIC	-915.215	
AICc	-914.865	

1.6 Note S6 - Assumptions and limitations

1.6.1 Lack of spatially-explicit environmental impacts and limits

Our analysis focused on four environmental limits (Table S2). These environmental limits and the eight relevant environmental indicators selected to represent them, 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 locally relevant environmental limits and their impacts at the regional level. For *TotalAgArea*, these were derived at the global level, without explicitly accounting for the three individual biomes of tropical, temperate and boreal forest [25]. Not accounting for local or regional impacts underestimates exceedance risk across spatially-dependent limits such as land-system change, surface water flows, and nutrient cycles, with recent work focusing on adding regional granularity to these relevant planetary and earth system boundaries [15,16,54].

While our estimates of environmental limits encompassed wide uncertainty ranges incorporated in published estimates as well as the full range in potential future shares of the global food system proxies (Table S2), studies highlight the added importance of process-detailed spatially explicit assessments to concurrently account for both local and global impacts [15,91,156,271]. Other work is also developing approaches to downscale planetary boundaries to the country-level [272-275]. A growing body of simulation results with harmonized country- and regional- level results from multi-model assessments [15,149,203,276], 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.

1.6.2 Omitted environmental limits

As a result of our focus on specific environmental limits, our analysis did not encompass the potential risk contribution of the food system on other key environmental indicators and limits. In addition to the four environmental limits explicitly quantified in our study, agriculture has been identified as a major contributor to impacts across several planetary boundaries including biosphere integrity, ocean acidification, stratospheric ozone depletion, and novel entities [23].

While the environmental limit for agricultural area is based on the land-system change planetary boundary which encompasses 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 [23,25,277]. Assessments have modelled global food system impacts on extinction rates [53] and the biodiversity intactness index (BII) [96,156,271,278], 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 [136,279], in addition to the many strong interactions of biosphere integrity with other environmental limits [16,280,281], 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 [23]. 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. 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 planetary boundary, contributing around 5% to stratospheric ozone depletion via the historical influence of chlorofluorocarbon emissions [23]. 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 [173,229]. Another class of chemicals widely used in agriculture—pesticides—are encompassed in the novel entities planetary boundary [25]. However, there is global-level indicator that could be used. While abundant fertilizer and some pesticide estimates [47,282] 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.

1.6.3 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 [89]. While feed efficiency and food-competing feed account for some of the unaccounted-for variance, a dedicated pasture productivity variable would likely 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 withdrawals in agriculture [109,222]. The water-use efficiency metric (see 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 (see 1.6.4).
- *Land-use regulation and conservation actions*. Stricter regulation of land use is a key measure to limit total agricultural area and reduce GHG emissions [283], this is currently under-represented in most models [149]. While this was partly accounted for through the use of a carbon price (see 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 nutrient cycles where nutrient-use efficiency has a non-linear relationship with N_{fert} because of the possibility of declining spatial efficiency of N across regions, as has been historically observed [198,284]. 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 [111], meaning that an assumed linear relationship between nutrient-use efficiency and P_{fert} may be an oversimplification.

1.6.4 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 [109,180]. 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 [88].
- *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 [136,285,286]. 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 [88]. 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 [287].

1.7 Note S7 - Supplemental result items

1.7.1 Base year and TREND predictions

Table S24. Base year and TREND (all interventions set to trend level) predictions 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)		
PB/ESB	**Indicator**	**Units**	**Mean estimate**	**Mean projection**	**Standard deviation**	**Risk of exceedance**
Land-system change	Cropland	Mha	1525[a]	1834	137	-
	Pasture	Mha	3259[a]	3409	544	-
	Total agricultural area	Mha	4784	5244	561	0.95
GHG emissions	Methane	Mt CO_2e yr^{-1}	4185[b]	4676	229	-
	Nitrous oxide	Mt CO_2e yr^{-1}	1916[b]	2592	209	-
	Land-use change	Mt CO_2 yr^{-1}	5460[c]	3567	1177	-
	Total direct agriculture emissions	Mt CO_2e	11561	12168	1184	1.00
Surface water flows	*Blue water withdrawals*	km^3 yr^{-1}	2700[d]	3871	200	0.32
Nutrient flows – N	Nitrogen fertiliser	Tg yr^{-1}	103.7[e]	132	12.0	1.00
Nutrient flows – P	Phosphorus fertiliser	Tg yr^{-1}	17.8[e]	22.9	1.95	1.00

[a] AR6 IAMC selected model average (see Table S6)
[b] AR6 IAMC selected model average (see Table S6) using AR6 GWP-100 factors [118]
[c] AR6 IAMC selected model average (see Table S6)
[d] AQUASTAT
[e] Springmann et al. (2018) [17]
[f] Springmann et al. (2018) [17]

1.7.2 Mitigation potential for sub-indicators across all intervention levels

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

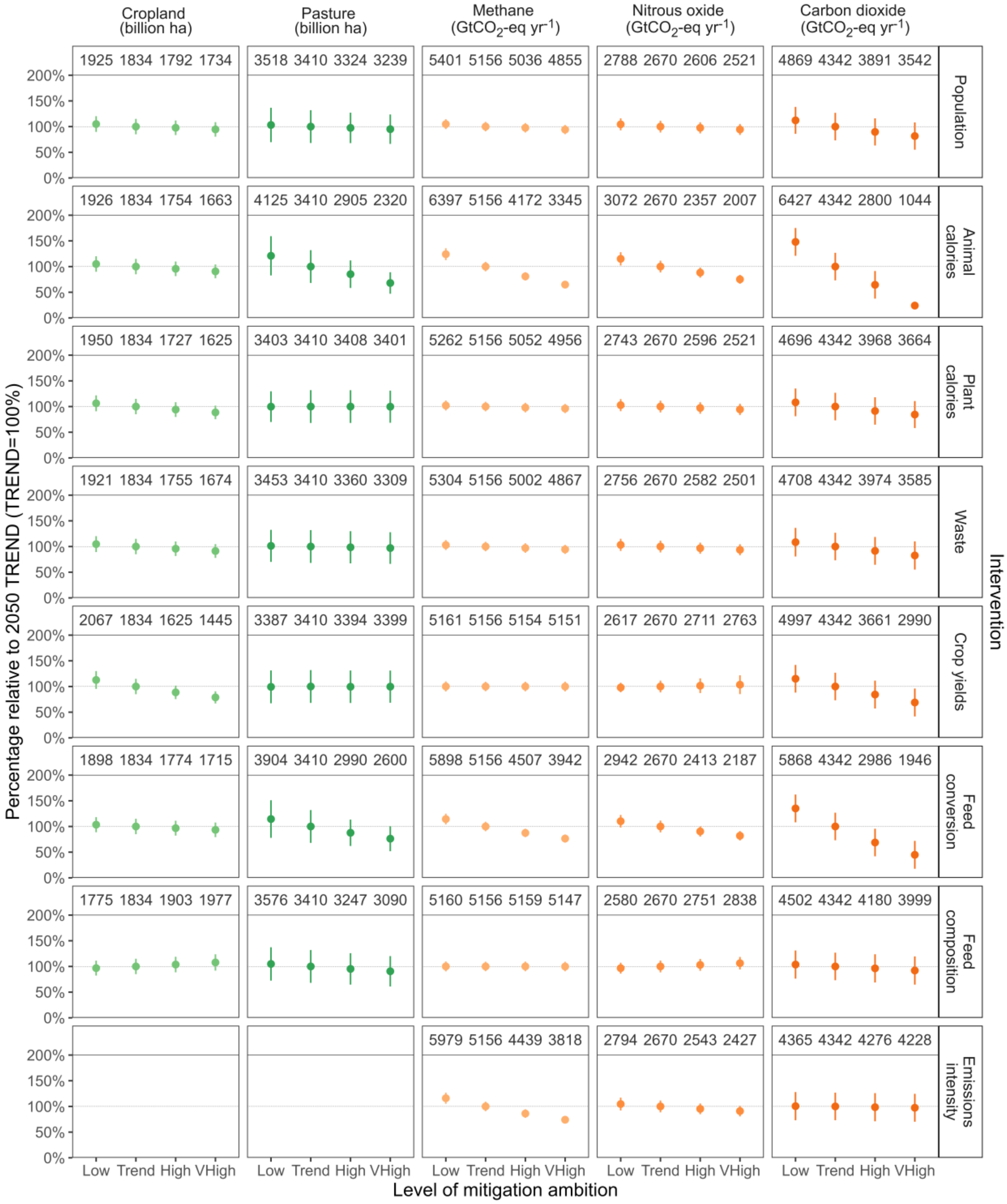


Fig. S4. Modeled mitigation potential in 2050 under a range of ambition levels for selected interventions for all sub-indicators of agricultural area (cropland, pasture) and greenhouse gas emissions (methane, nitrous oxide, and carbon dioxide from land-use change). Data are presented as mean predictions (bubbles) and 95% (± 2 SD) bootstrap prediction intervals (vertical lines). Black numbers at the top of panels indicate pressure in physical units (e.g. billion ha for agricultural area). Empty panels correspond to interventions excluded from individual models due to lack of relevance, or missing/insufficient data. The vertical lines for carbon dioxide correspond to the 68% (± 1 SD) prediction intervals to facilitate the readability of the graph. See Data S4 for full prediction dataset.

1.7.3 Final mapping of risk-compliant combinations

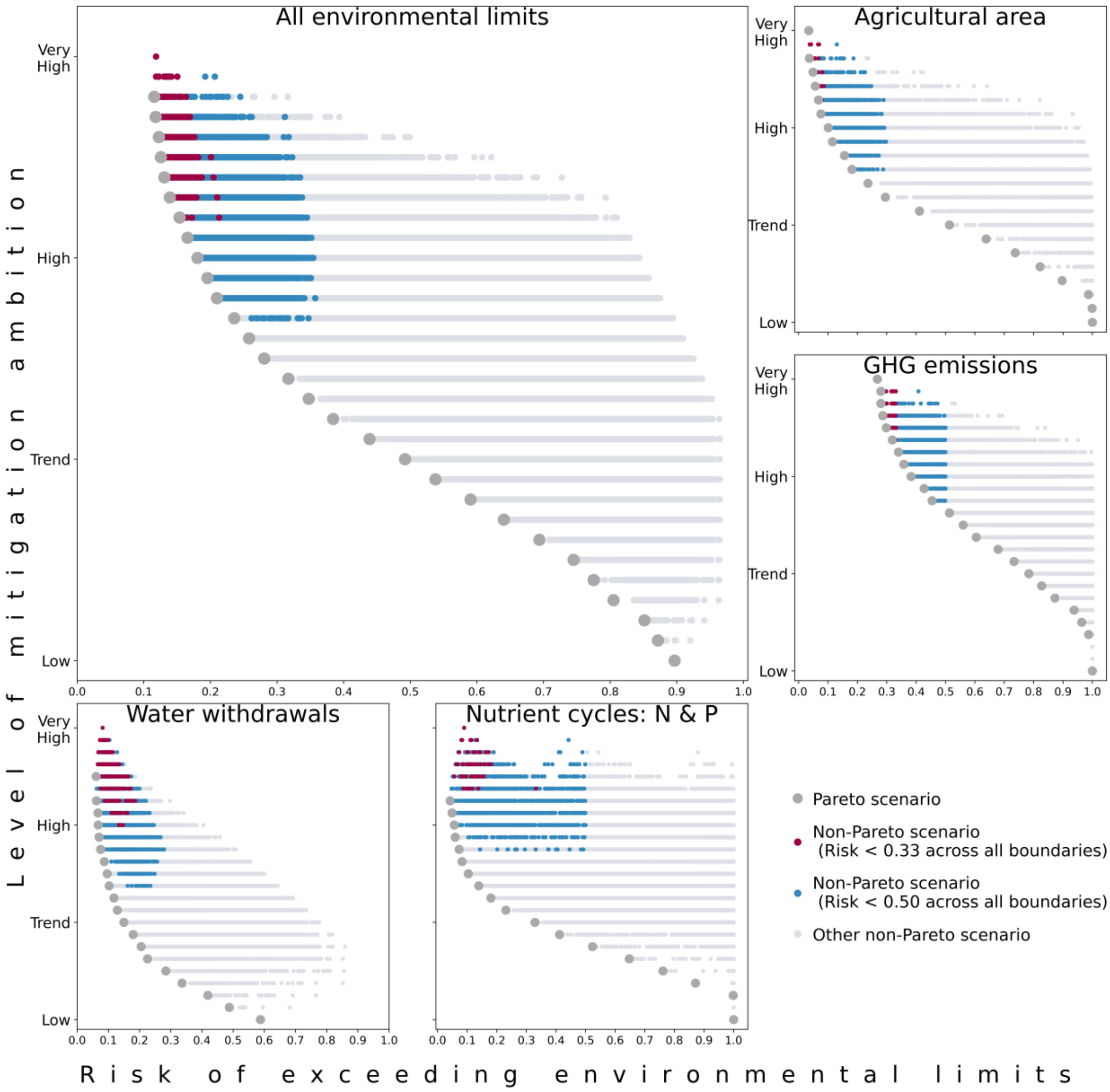


Fig. S5. Trade-offs between average mitigation ambition and risk reduction for all environmental limits. Shown are the combined Pareto front which assumes equal-priority weighting of all four environmental limits (large panel, n = 1,048,576), and Pareto fronts for each environmental limit (smaller panels, where $n = 4^7 = 16{,}384$ for agricultural area, $n = 4^8 = 65{,}536$ for GHG emissions, $n = 4^8 = 65{,}536$ for water withdrawals, and $n = 4^8 = 65{,}536$ for nutrient cycles. 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 [151], 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*). The clouds of light grey dots are all the scenarios that do not belong to the Pareto set and exceed the 0.5 condition for at least one environmental limit.

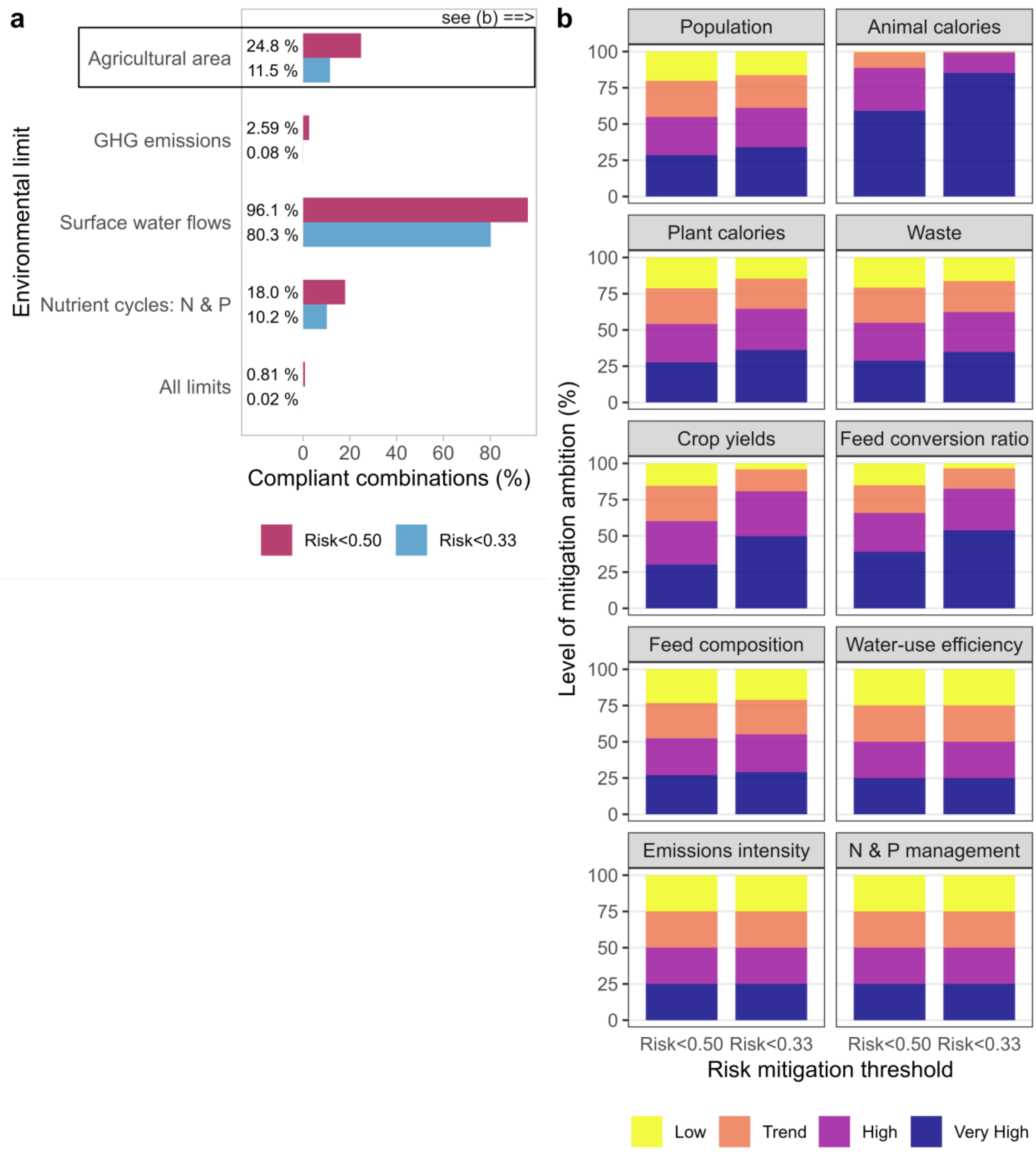


Fig. S6. Percentages of risk-compliant combinations and required intervention ambition levels to meet alternative risk thresholds. **a**. The horizontal bar plot displays the percentage out of a total of 1,048,576 plausible combinations that meet each of the two risk thresholds (risk < 0.50 and risk < 0.33) for each environmental limit and combined for all limits. **b**. The vertical bar plots display the percentages of each of the four levels (Low, Trend, High, Very High) of mitigation ambition for the intervention combinations that meet each of the two risk thresholds for Agricultural area.

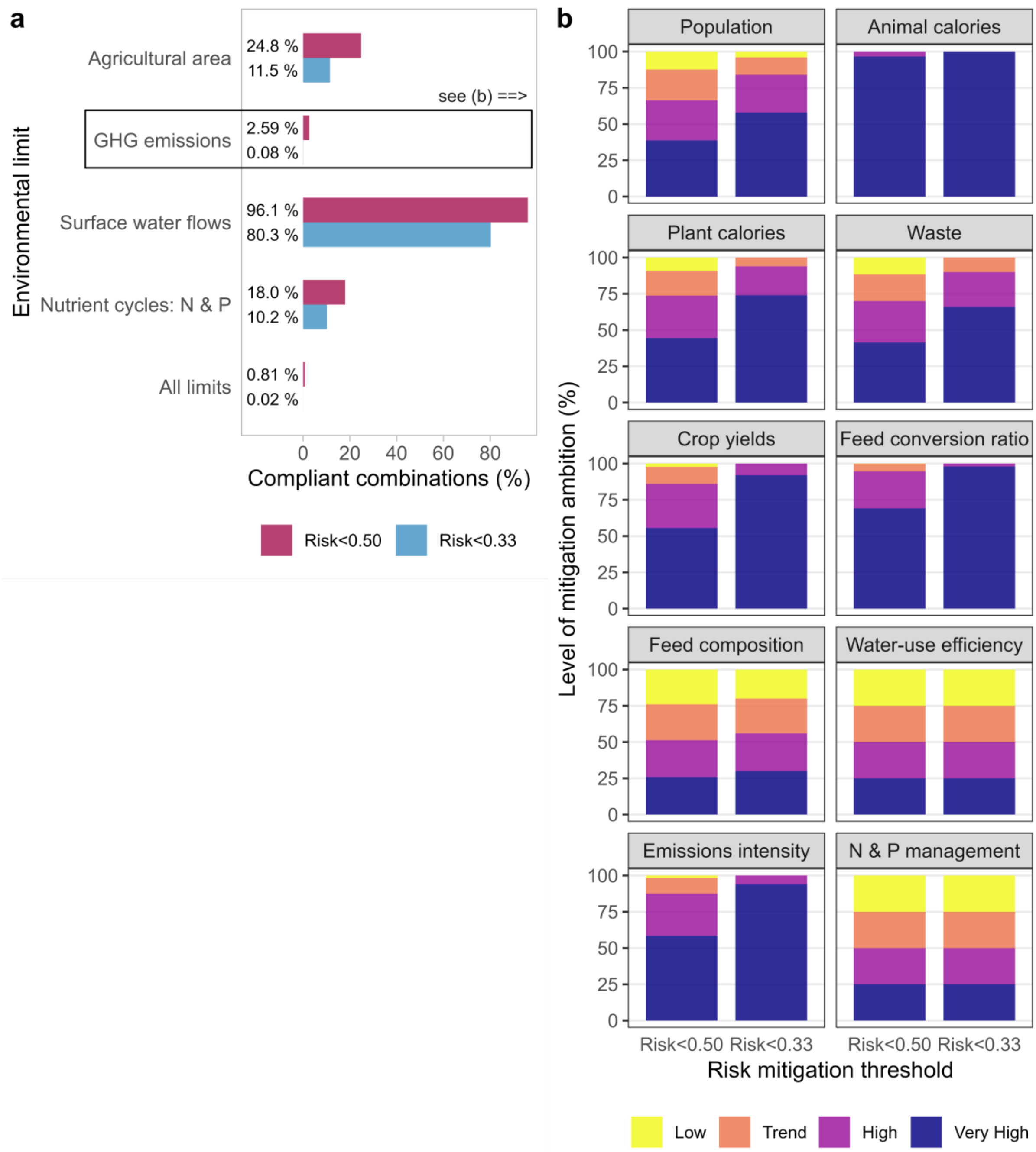


Fig. S7. Percentages of risk-compliant combinations and required intervention ambition levels to meet alternative risk thresholds. **a**. The horizontal bar plot displays the percentage out of a total of 1,048,576 plausible combinations that meet each of the two risk thresholds (risk < 0.50 and risk < 0.33) for each environmental limit and combined for all limits. **b**. The vertical bar plots display the percentages of each of the four levels (Low, Trend, High, Very High) of mitigation ambition for the intervention combinations that meet each of the two risk thresholds for GHG emissions.

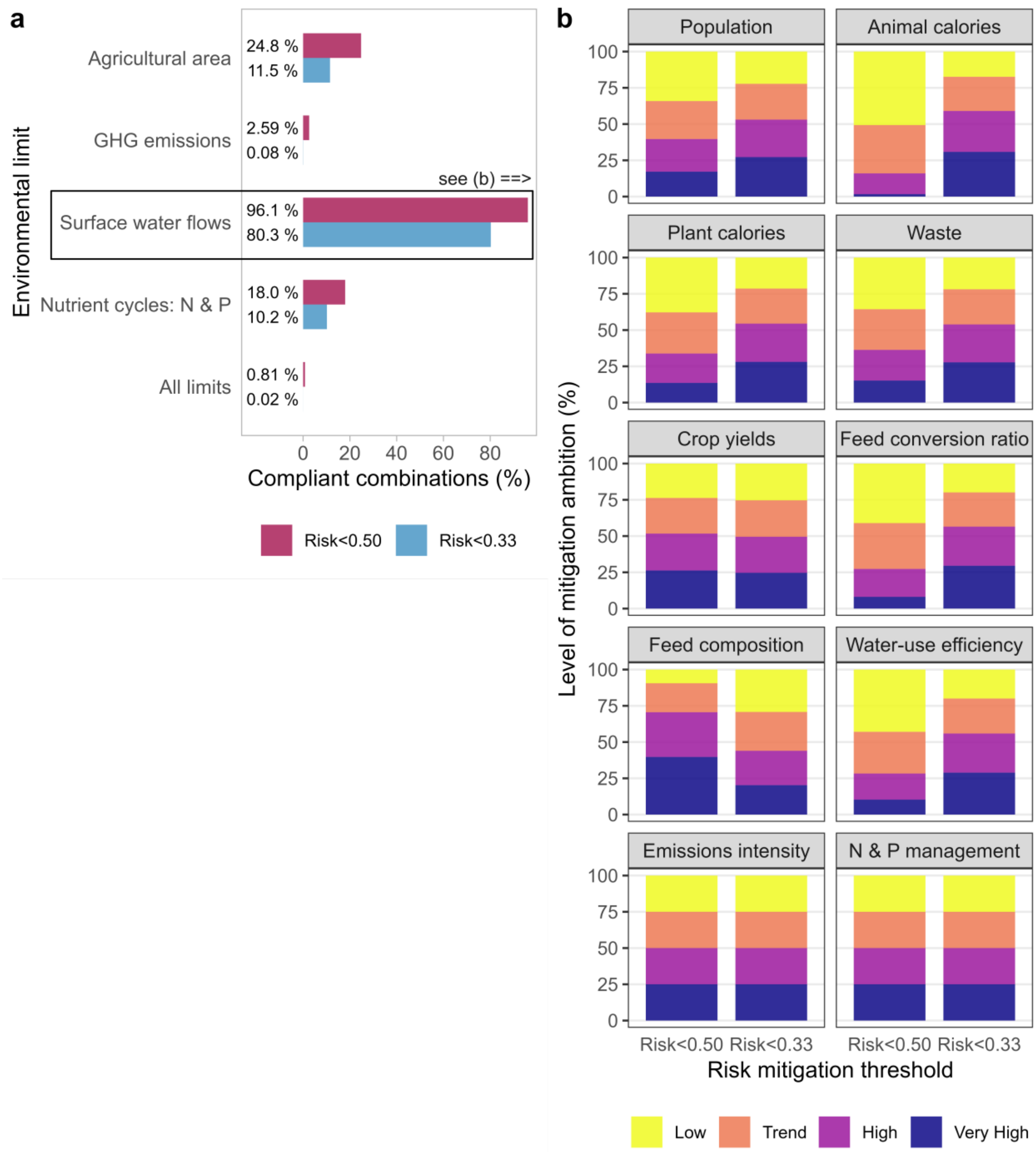


Fig. S8. Percentages of risk-compliant combinations and required intervention ambition levels to meet alternative risk thresholds. **a**. The horizontal bar plot displays the percentage out of a total of 1,048,576 plausible combinations that meet each of the two risk thresholds (risk < 0.50 and risk < 0.33) for each environmental limit and combined for all limits. **b**. The vertical bar plots display the percentages of each of the four levels (Low, Trend, High, Very High) of mitigation ambition for the intervention combinations that meet each of the two risk thresholds for surface water flows.

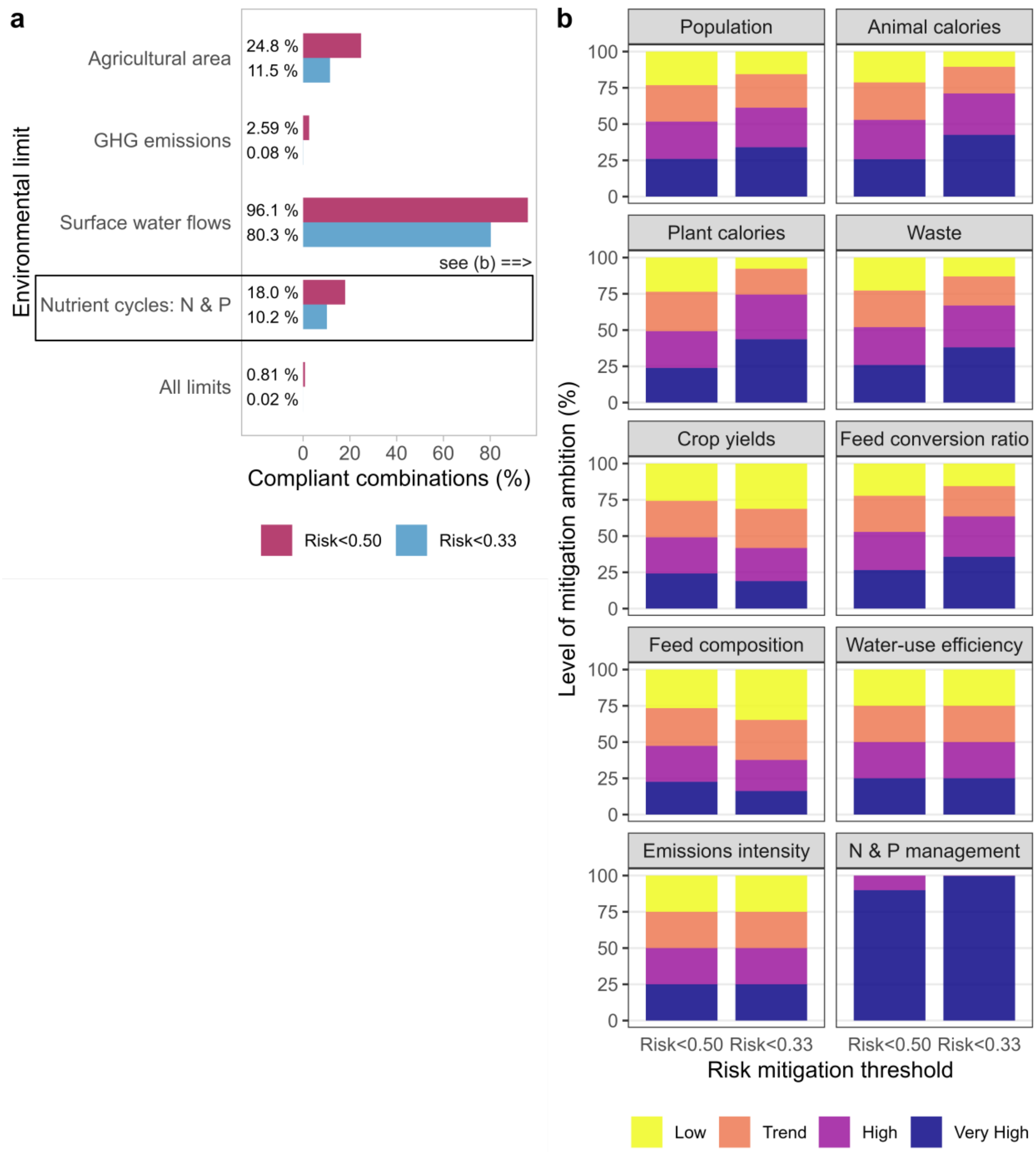


Fig. S9. Percentages of risk-compliant combinations and required intervention ambition levels to meet alternative risk thresholds. **a**. The horizontal bar plot displays the percentage out of a total of 1,048,576 plausible combinations that meet each of the two risk thresholds (risk < 0.50 and risk < 0.33) for each environmental limit and combined for all limits. **b**. The vertical bar plots display the percentages of each of the four levels (Low, Trend, High, Very High) of mitigation ambition for the intervention combinations that meet each of the two risk thresholds for nutrient cycles.

2 Supplemental references

1. Van Den Bergh, J.C.J.M., and Rietveld, P. (2004). Reconsidering the Limits to World Population: Meta-analysis and Meta-prediction. BioScience *54*, 195-204. 10.1641/0006-3568(2004)054[0195:RTLTWP]2.0.CO;2.
2. Seto, K.C., Fragkias, M., Güneralp, B., and Reilly, M.K. (2011). A Meta-Analysis of Global Urban Land Expansion. PLoS ONE *6*, e23777. 10.1371/journal.pone.0023777.
3. van Dijk, M., Morley, T., Rau, M.L., and Saghai, Y. (2021). A meta-analysis of projected global food demand and population at risk of hunger for the period 2010–2050. Nat. Food *2*, 494-501. 10.1038/s43016-021-00322-9.
4. James, K.L., Randall, N.P., and Haddaway, N.R. (2016). A methodology for systematic mapping in environmental sciences. Environ. Evid. *5*, 7. 10.1186/s13750-016-0059-6.
5. CEE (2013). Guidelines for Systematic Review and Evidence Synthesis in Environmental Management (Version 4.2). Collaboration for Environmental Evidence (CEE).
6. Koricheva, J., Gurevitch, J., and Mengersen, K. (2013). Handbook of Meta-analysis in Ecology and Evolution (Princeton University Press).
7. Gurevitch, J., Koricheva, J., Nakagawa, S., and Stewart, G. (2018). Meta-analysis and the science of research synthesis. Nature *555*, 175. 10.1038/nature25753.
8. Tuomisto, H.L., Hodge, I.D., Riordan, P., and Macdonald, D.W. (2012). Does organic farming reduce environmental impacts? – A meta-analysis of European research. J. Environ. Manage. *112*, 309-320. https://doi.org/10.1016/j.jenvman.2012.08.018.
9. Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., and The, P.G. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med. *6*, e1000097. 10.1371/journal.pmed.1000097.
10. Livoreil, B., Glanville, J., Haddaway, N.R., Bayliss, H., Bethel, A., de Lachapelle, F.F., Robalino, S., Savilaakso, S., Zhou, W., Petrokofsky, G., and Frampton, G. (2017). Systematic searching for environmental evidence using multiple tools and sources. Environ. Evid. *6*, 23. 10.1186/s13750-017-0099-6.
11. Clune, S., Crossin, E., and Verghese, K. (2017). Systematic review of greenhouse gas emissions for different fresh food categories. J. Clean. Prod. *140, Part 2*, 766-783. http://dx.doi.org/10.1016/j.jclepro.2016.04.082.
12. Hallström, E., Carlsson-Kanyama, A., and Börjesson, P. (2015). Environmental impact of dietary change: a systematic review. J. Clean. Prod. *91*, 1-11. http://dx.doi.org/10.1016/j.jclepro.2014.12.008.
13. Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., et al. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ *372*, n71. 10.1136/bmj.n71.
14. Rockström, J., Donges, J.F., Fetzer, I., Martin, M.A., Wang-Erlandsson, L., and Richardson, K. (2024). Planetary Boundaries guide humanity's future on Earth. Nat. Rev. Earth Environ. *5*, 773-788. 10.1038/s43017-024-00597-z.
15. Rockström, J., Gupta, J., Qin, D., Lade, S.J., Abrams, J.F., Andersen, L.S., Armstrong McKay, D.I., Bai, X., Bala, G., Bunn, S.E., et al. (2023). Safe and just Earth system boundaries. Nature *619*, 102-111. 10.1038/s41586-023-06083-8.
16. Richardson, K., Steffen, W., Lucht, W., Bendtsen, J., Cornell, S.E., Donges, J.F., Drüke, M., Fetzer, I., Bala, G., von Bloh, W., et al. (2023). Earth beyond six of nine planetary boundaries. Sci. Adv. *9*, eadh2458. doi:10.1126/sciadv.adh2458.
17. Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B.L., Lassaletta, L., de Vries, W., Vermeulen, S.J., Herrero, M., Carlson, K.M., et al. (2018). Options for keeping the food system within environmental limits. Nature *562*, 519-525. 10.1038/s41586-018-0594-0.
18. Schardt, C., Adams, M.B., Owens, T., Keitz, S., and Fontelo, P. (2007). Utilization of the PICO framework to improve searching PubMed for clinical questions. BMC Med. Inform. Decis. Mak. *7*, 16. 10.1186/1472-6947-7-16.
19. Merli, R., Preziosi, M., and Acampora, A. (2017). How do scholars approach the circular economy? A systematic literature review. J. Clean. Prod. *178*, 703-722. https://doi.org/10.1016/j.jclepro.2017.12.112.
20. Le Mouël, C., and Forslund, A. (2017). How can we feed the world in 2050? A review of the responses from global scenario studies. Eur. Rev. Agric. Econ. *44*, 541-591. 10.1093/erae/jbx006.
21. Pickering, C., and Byrne, J. (2014). The benefits of publishing systematic quantitative literature reviews for PhD candidates and other early-career researchers. High. Educ. Res. Dev. *33*, 534-548. 10.1080/07294360.2013.841651.

22. Borenstein, M., Hedges, L.V., Higgins, J.P., and Rothstein, H.R. (2009). Introduction to Meta-Analysis (John Wiley & Sons).
23. Campbell, B.M., Beare, D.J., Bennett, E.M., Hall-Spencer, J.M., Ingram, J.S.I., Jaramillo, F., Ortiz, R., Ramankutty, N., Sayer, J.A., and Shindell, D. (2017). Agriculture production as a major driver of the Earth system exceeding planetary boundaries. Ecol. Soc. *22*, 8, 8. 10.5751/ES-09595-220408.
24. Rockström, J., Steffen, W., Noone, K., Persson, A., Chapin, F.S., Lambin, E.F., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J., et al. (2009). A safe operating space for humanity. Nature *461*, 472-475.
25. Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., de Vries, W., de Wit, C.A., et al. (2015). Planetary boundaries: Guiding human development on a changing planet. Science *347*. 10.1126/science.1259855.
26. Stein, W.E., and Keblis, M.F. (2009). A new method to simulate the triangular distribution. Math. Comput. Model. *49*, 1143-1147. https://doi.org/10.1016/j.mcm.2008.06.013.
27. Fairchild, K.W., Misra, L., and Shi, Y. (2016). Using Triangular Distribution for Business and Finance Simulations in Excel. J. Financ. Educ. *42*, 313-336.
28. Jannat, S., and Greenwood, A.G. (2012). Estimating parameters of the triangular distribution using nonstandard information. Proceedings of the Winter Simulation Conference. Winter Simulation Conference.
29. Byers, E., Krey, V., Kriegler, E., Riahi, K., Schaeffer, R., Kikstra, J., Lamboll, R., Nicholls, Z., Sanstad, M., Smith, C., et al. (2022). AR6 Scenarios Database hosted by IIASA. International Institute for Applied Systems Analysis.
30. Spiess, A.-N. (2018). propagate: Propagation of Uncertainty. R package version 1.0-6.
31. Freedman, D., and Diaconis, P. (1981). On the histogram as a density estimator:L2 theory. Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete *57*, 453-476. 10.1007/bf01025868.
32. Wells, J.R., and Ting, K.M. (2017). A simple efficient density estimator that enables fast systematic search. arXiv preprint arXiv:1707.00783.
33. Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Kriegler, E., et al. (2018). Mitigation pathways compatible with 1.5°C in the context of sustainable development. In Special Report on the impacts of global warming of 1.5 °C, (Intergovernmental Panel on Climate Change).
34. Clark, M.A., Domingo, N.G.G., Colgan, K., Thakrar, S.K., Tilman, D., Lynch, J., Azevedo, I.L., and Hill, J.D. (2020). Global food system emissions could preclude achieving the 1.5° and 2°C climate change targets. Science *370*, 705-708. 10.1126/science.aba7357.
35. Chang, J., Havlík, P., Leclère, D., de Vries, W., Valin, H., Deppermann, A., Hasegawa, T., and Obersteiner, M. (2021). Reconciling regional nitrogen boundaries with global food security. Nat. Food *2*, 700-711. 10.1038/s43016-021-00366-x.
36. Gerten, D., and Kummu, M. (2021). Feeding the world in a narrowing safe operating space. One Earth *4*, 1193-1196. https://doi.org/10.1016/j.oneear.2021.08.020.
37. Conijn, J.G., Bindraban, P.S., Schröder, J.J., and Jongschaap, R.E.E. (2018). Can our global food system meet food demand within planetary boundaries? Agric. Ecosyst. Environ. *251*, 244-256. https://doi.org/10.1016/j.agee.2017.06.001.
38. Zhang, Q., Qi, J., Cheng, B., Yu, C., Liang, S., Wiedmann, T.O., Liu, Y., and Zhong, Q. (2021). Planetary Boundaries for Forests and Their National Exceedance. Environ. Sci. Techno. *55*, 15423-15434. 10.1021/acs.est.1c02513.
39. FAO (2021). FAOSTAT Land Use Domain.
40. Ramankutty, N., Evan, A.T., Monfreda, C., and Foley, J.A. (2008). Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. Global Biogeochem. Cycles *22*. doi:10.1029/2007GB002952.
41. Curtis, P.G., Slay, C.M., Harris, N.L., Tyukavina, A., and Hansen, M.C. (2018). Classifying drivers of global forest loss. Science *361*, 1108-1111. 10.1126/science.aau3445.
42. Hosonuma, N., Herold, M., De Sy, V., De Fries, R.S., Brockhaus, M., Verchot, L., Angelsen, A., and Romijn, E. (2012). An assessment of deforestation and forest degradation drivers in developing countries. Environ. Res. Lett. *7*, 044009. 10.1088/1748-9326/7/4/044009.
43. Kissinger, G., Herold, M., and De Sy, V. (2012). Drivers of Deforestation and Forest Degradation: A Synthesis Report for REDD+ Policymakers. Lexeme Consulting.
44. Geist, H.J., and Lambin, E.F. (2002). Proximate Causes and Underlying Driving Forces of Tropical Deforestation: Tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. BioScience *52*, 143-150. 10.1641/0006-3568(2002)052[0143:Pcaudf]2.0.Co;2.

45. UNCCD (2017). The Global Land Outlook, first edition. United Nations Convention to Combat Desertification.
46. Crippa, M., Solazzo, E., Guizzardi, D., Monforti-Ferrario, F., Tubiello, F.N., and Leip, A. (2021). Food systems are responsible for a third of global anthropogenic GHG emissions. Nat. Food *2*, 198-209. 10.1038/s43016-021-00225-9.
47. Muller, A., Schader, C., El-Hage Scialabba, N., Brüggemann, J., Isensee, A., Erb, K.-H., Smith, P., Klocke, P., Leiber, F., Stolze, M., and Niggli, U. (2017). Strategies for feeding the world more sustainably with organic agriculture. Nat. Commun. *8*, 1290. 10.1038/s41467-017-01410-w.
48. Schader, C., Muller, A., Scialabba, N.E.-H., Hecht, J., Isensee, A., Erb, K.-H., Smith, P., Makkar, H.P.S., Klocke, P., Leiber, F., et al. (2015). Impacts of feeding less food-competing feedstuffs to livestock on global food system sustainability. J. R. Soc. Interface *12*. 10.1098/rsif.2015.0891.
49. Kopittke, P.M., Menzies, N.W., Dalal, R.C., McKenna, B.A., Husted, S., Wang, P., and Lombi, E. (2021). The role of soil in defining planetary boundaries and the safe operating space for humanity. Environ. Int. *146*, 106245. https://doi.org/10.1016/j.envint.2020.106245.
50. Pendrill, F., Gardner, T.A., Meyfroidt, P., Persson, U.M., Adams, J., Azevedo, T., Bastos Lima, M.G., Baumann, M., Curtis, P.G., De Sy, V., et al. (2022). Disentangling the numbers behind agriculture-driven tropical deforestation. Science *377*, eabm9267. doi:10.1126/science.abm9267.
51. Niazi, H., Wild, T.B., Turner, S.W.D., Graham, N.T., Hejazi, M., Msangi, S., Kim, S., Lamontagne, J.R., and Zhao, M. (2024). Global peak water limit of future groundwater withdrawals. Nat. Sustain. *7*, 413-422. 10.1038/s41893-024-01306-w.
52. Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., et al. (2015). Mapping global cropland and field size. *21*, 1980-1992. doi:10.1111/gcb.12838.
53. Willett, W., Rockström, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., Garnett, T., Tilman, D., DeClerck, F., Wood, A., et al. (2019). Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. The Lancet *393*, 447-492. 10.1016/S0140-6736(18)31788-4.
54. Porkka, M., Virkki, V., Wang-Erlandsson, L., Gerten, D., Gleeson, T., Mohan, C., Fetzer, I., Jaramillo, F., Staal, A., te Wierik, S., et al. (2024). Notable shifts beyond pre-industrial streamflow and soil moisture conditions transgress the planetary boundary for freshwater change. Nature Water *2*, 262-273. 10.1038/s44221-024-00208-7.
55. Wisser, D., Fekete, B.M., Vörösmarty, C.J., and Schumann, A.H. (2010). Reconstructing 20th century global hydrography: a contribution to the Global Terrestrial Network- Hydrology (GTN-H). Hydrol. Earth Syst. Sci. *14*, 1-24. 10.5194/hess-14-1-2010.
56. Abatzoglou, J.T., Dobrowski, S.Z., Parks, S.A., and Hegewisch, K.C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. Scientific Data *5*, 170191. 10.1038/sdata.2017.191.
57. Richter, B.D., Davis, M.M., Apse, C., and Konrad, C. (2012). A presumptive standard for environmental flow protection. River Research and Applications *28*, 1312-1321. https://doi.org/10.1002/rra.1511.
58. Richter, B.D., Davis, M.M., Apse, C., and Konrad, C. (2011). A Presumptive Standard for Environmental Flow Protection. River Research and Applications *28*, 1312-1321. 10.1002/rra.1511.
59. Bogardi, J.J., Fekete, B.M., and Vörösmarty, C.J. (2013). Planetary boundaries revisited: a view through the 'water lens'. Curr. Opin. Environ. Sustain. *5*, 581-589. https://doi.org/10.1016/j.cosust.2013.10.006.
60. IAASTD. (2009). Agriculture at a Crossroads: Global Report (Island Press).
61. Ercin, A.E., and Hoekstra, A.Y. (2014). Water footprint scenarios for 2050: A global analysis. Environ. Int. *64*, 71-82. https://doi.org/10.1016/j.envint.2013.11.019.
62. Bijl, D.L., Biemans, H., Bogaart, P.W., Dekker, S.C., Doelman, J.C., Stehfest, E., and van Vuuren, D.P. (2018). A Global Analysis of Future Water Deficit Based On Different Allocation Mechanisms. Water Resour. Res. *54*, 5803-5824. doi:10.1029/2017WR021688.
63. Bijl, D.L., Bogaart, P.W., Kram, T., de Vries, B.J.M., and van Vuuren, D.P. (2016). Long-term water demand for electricity, industry and households. Environ. Sci. Policy *55*, 75-86. https://doi.org/10.1016/j.envsci.2015.09.005.
64. Shen, Y., Oki, T., Kanae, S., Hanasaki, N., Utsumi, N., and Kiguchi, M. (2014). Projection of future world water resources under SRES scenarios: an integrated assessment. Hydrol. Sci. J. *59*, 1775-1793. 10.1080/02626667.2013.862338.
65. Alcamo, J., Fiorke, M., and Marker, M. (2007). Future long-term changes in global water resources driven by socio-economic and climatic changes. Hydrol. Sci. J. *52*, 247-275. 10.1623/hysj.52.2.247.

66. Hanasaki, N., Fujimori, S., Yamamoto, T., Yoshikawa, S., Masaki, Y., Hijioka, Y., Kainuma, M., Kanamori, Y., Masui, T., Takahashi, K., and Kanae, S. (2013). A global water scarcity assessment under Shared Socio-economic Pathways – Part 1: Water use. Hydrol. Earth Syst. Sci. *17*, 2375-2391. 10.5194/hess-17-2375-2013.
67. de Fraiture, C., Wichelns, D., Rockstrom, J., Kemp-Benedict, E., Eriyagama, N., Gordon, L.J., Hanjra, M.A., Hoogeveen, J., Huber-Lee, A., and Karlberg, L. (2007). Looking ahead to 2050: scenarios of alternative investment approaches. In Water for Food, Water for Life: A Comprehensive Assessment of Water Management in Agriculture, D. Molden, ed. (Earthscan and International Water Management Institute).
68. Graham, N.T., Davies, E.G.R., Hejazi, M.I., Calvin, K., Kim, S.H., Helinski, L., Miralles-Wilhelm, F.R., Clarke, L., Kyle, P., Patel, P., et al. (2018). Water Sector Assumptions for the Shared Socioeconomic Pathways in an Integrated Modeling Framework. Water Resour. Res. *54*, 6423-6440. doi:10.1029/2018WR023452.
69. Graham, N.T., Iyer, G., Wild, T.B., Dolan, F., Lamontagne, J., and Calvin, K. (2023). Agricultural market integration preserves future global water resources. One Earth *6*, 1235-1245. https://doi.org/10.1016/j.oneear.2023.08.003.
70. Hejazi, M., Edmonds, J., Clarke, L., Kyle, P., Davies, E., Chaturvedi, V., Wise, M., Patel, P., Eom, J., Calvin, K., et al. (2014). Long-term global water projections using six socioeconomic scenarios in an integrated assessment modeling framework. Technol. Forecast. Soc. Change *81*, 205-226. https://doi.org/10.1016/j.techfore.2013.05.006.
71. Döll, P., Hoffmann-Dobrev, H., Portmann, F.T., Siebert, S., Eicker, A., Rodell, M., Strassberg, G., and Scanlon, B.R. (2012). Impact of water withdrawals from groundwater and surface water on continental water storage variations. Journal of Geodynamics *59-60*, 143-156. https://doi.org/10.1016/j.jog.2011.05.001.
72. Grogan, D.S., Wisser, D., Prusevich, A., Lammers, R.B., and Frolking, S. (2017). The use and re-use of unsustainable groundwater for irrigation: a global budget. Environ. Res. Lett. *12*, 034017. 10.1088/1748-9326/aa5fb2.
73. Turner, S.W.D., Hejazi, M., Yonkofski, C., Kim, S.H., and Kyle, P. (2019). Influence of Groundwater Extraction Costs and Resource Depletion Limits on Simulated Global Nonrenewable Water Withdrawals Over the Twenty-First Century. Earth's Future *7*, 123-135. https://doi.org/10.1029/2018EF001105.
74. Stewart-Koster, B., Bunn, S.E., Green, P., Ndehedehe, C., Andersen, L.S., Armstrong McKay, D.I., Bai, X., DeClerck, F., Ebi, K.L., Gordon, C., et al. (2024). Living within the safe and just Earth system boundaries for blue water. Nat. Sustain. *7*, 53-63. 10.1038/s41893-023-01247-w.
75. Zurek, M., Hebinck, A., and Selomane, O. (2022). Climate change and the urgency to transform food systems. Science *376*, 1416-1421. doi:10.1126/science.abo2364.
76. Stevanović, M., Popp, A., Bodirsky, B.L., Humpenöder, F., Müller, C., Weindl, I., Dietrich, J.P., Lotze-Campen, H., Kreidenweis, U., Rolinski, S., et al. (2017). Mitigation Strategies for Greenhouse Gas Emissions from Agriculture and Land-Use Change: Consequences for Food Prices. Environ. Sci. Techno. *51*, 365-374. 10.1021/acs.est.6b04291.
77. Bajzelj, B., Richards, K.S., Allwood, J.M., Smith, P., Dennis, J.S., Curmi, E., and Gilligan, C.A. (2014). Importance of food-demand management for climate mitigation. Nat. Clim. Chang. *4*, 924-929. http://dx.doi.org/10.1038/nclimate2353.
78. Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E.A., Haberl, H., Harper, R., House, J., Jafari, M., et al. (2014). Agriculture, Forestry and Other Land Use (AFOLU). In Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel, J.C. Minx, ed. (Cambridge University Press).
79. Roe, S., Streck, C., Beach, R., Busch, J., Chapman, M., Daioglou, V., Deppermann, A., Doelman, J., Emmet-Booth, J., Engelmann, J., et al. (2021). Land-based measures to mitigate climate change: Potential and feasibility by country. Glob. Chang. Biol. *27*, 6025-6058.
80. Wollenberg, E., Richards, M., Smith, P., Havlík, P., Obersteiner, M., Tubiello, F.N., Herold, M., Gerber, P., Carter, S., Reisinger, A., et al. (2016). Reducing emissions from agriculture to meet the 2 °C target. Glob. Chang. Biol. *22*, 3859-3864. 10.1111/gcb.13340.
81. Frank, S., Havlík, P., Soussana, J.-F., Levesque, A., Valin, H., Wollenberg, E., Kleinwechter, U., Fricko, O., Gusti, M., Herrero, M., et al. (2017). Reducing greenhouse gas emissions in agriculture without compromising food security? Environ. Res. Lett. *12*, 105004.

82. Guivarch, C., Kriegler, E., Portugal-Pereira, J., Bosetti, V., Edmonds, J., Fischedick, M., Havlík, P., Jaramillo, P., Krey, V., Lecocq, F., et al. (2022). Annex III: Scenarios and modelling methods. In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, ed. (Cambridge University Press).
83. Nabuurs, G.-J., R. Mrabet, A. Abu Hatab, M. Bustamante, H. Clark, P. Havlík, J. House, C. Mbow, K.N. Ninan, A. Popp, S. Roe, B. Sohngen, S. Towprayoon (2022). Agriculture, Forestry and Other Land Uses (AFOLU). In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, ed. (Cambridge University Press).
84. IPCC (2019). Special Report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. Intergovernmental Panel on Climate Change.
85. Huppmann, D., Rogelj, J., Krey, V., Kriegler, E., and Riahi, K. (2018). A new scenario resource for integrated 1.5 °C research. Nat. Clim. Chang. 10.1038/s41558-018-0317-4.
86. Huppmann, D., Kriegler, E., Krey, V., Riahi, K., Rogelj, J., Rose, S.K., Weyant, J., Bauer, N., Bertram, C., Bosetti, V., et al. (2018). IAMC 1.5°C Scenario Explorer and Data hosted by IIASA. Integrated Assessment Modeling Consortium & International Institute for Applied Systems Analysis.
87. van Vuuren, D.P., Stehfest, E., Gernaat, D.E.H.J., van den Berg, M., Bijl, D.L., de Boer, H.S., Daioglou, V., Doelman, J.C., Edelenbosch, O.Y., Harmsen, M., et al. (2018). Alternative pathways to the 1.5 °C target reduce the need for negative emission technologies. Nat. Clim. Chang. *8*, 391-397. 10.1038/s41558-018-0119-8.
88. Poore, J., and Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. Science *360*, 987-992. 10.1126/science.aaq0216.
89. Tilman, D., and Clark, M. (2014). Global diets link environmental sustainability and human health. Nature *515*, 518-522. http://dx.doi.org/10.1038/nature13959.
90. Springmann, M., Godfray, H.C.J., Rayner, M., and Scarborough, P. (2016). Analysis and valuation of the health and climate change cobenefits of dietary change. Proc. Natl. Acad. Sci. U.S.A., 201523119. 10.1073/pnas.1523119113.
91. Schulte-Uebbing, L.F., Beusen, A.H.W., Bouwman, A.F., and de Vries, W. (2022). From planetary to regional boundaries for agricultural nitrogen pollution. Nature *610*, 507-512. 10.1038/s41586-022-05158-2.
92. de Vries, W., Kros, J., Kroeze, C., and Seitzinger, S.P. (2013). Assessing planetary and regional nitrogen boundaries related to food security and adverse environmental impacts. Curr. Opin. Environ. Sustain. *5*, 392-402. http://dx.doi.org/10.1016/j.cosust.2013.07.004.
93. Hubert, B., Rosegrant, M., van Boekel, M.A.J.S., and Ortiz, R. (2010). The Future of Food: Scenarios for 2050. Crop Sci. *50*, S-33-S-50. 10.2135/cropsci2009.09.0530.
94. van Dijk, M., and Meijerink, G.W. (2014). A review of global food security scenario and assessment studies: Results, gaps and research priorities. Glob. Food Sec. *3*, 227-238. http://dx.doi.org/10.1016/j.gfs.2014.09.004.
95. van Vuuren, D.P., Kok, M.T.J., Girod, B., Lucas, P.L., and de Vries, B. (2012). Scenarios in Global Environmental Assessments: Key characteristics and lessons for future use. Glob. Environ. Chang. *22*, 884-895. https://doi.org/10.1016/j.gloenvcha.2012.06.001.
96. Weindl, I., Soergel, B., Ambrósio, G., Daioglou, V., Doelman, J.C., Beier, F., Beusen, A., Bodirsky, B.L., Bos, A., Dietrich, J.P., et al. (2024). Food and land system transformations under different societal perspectives on sustainable development. Environ. Res. Lett.
97. Röös, E., Bajželj, B., Smith, P., Patel, M., Little, D., and Garnett, T. (2017). Greedy or needy? Land use and climate impacts of food in 2050 under different livestock futures. Glob. Environ. Chang. *47*, 1-12. https://doi.org/10.1016/j.gloenvcha.2017.09.001.
98. Erb, K.-H., Matej, S., Haberl, H., and Gingrich, S. (2024). Sustainable land systems in the Anthropocene: Navigating the global land squeeze. One Earth *7*, 1170-1186. 10.1016/j.oneear.2024.06.011.
99. Searchinger, T., Waite, R., Hanson, C., Ranganathan, J., Dumas, P., and Matthews, E. (2018). Creating a Sustainable Food Future: A Menu of Solutions to Feed Nearly 10 Billion People by 2050. World Resources Institute. https://www.wri.org/publication/creating-sustainable-food-future.
100. FOLU (2019). Growing Better: Ten Critical Transitions to Transform Food and Land Use. The Global Consultation Report of the Food and Land Use Coalition.

101. Pradhan, P., Fischer, G., van Velthuizen, H., Reusser, D.E., and Kropp, J.P. (2015). Closing Yield Gaps: How Sustainable Can We Be? PLoS ONE *10*, e0129487. 10.1371/journal.pone.0129487.
102. Zhang, X., Davidson, E.A., Mauzerall, D.L., Searchinger, T.D., Dumas, P., and Shen, Y. (2015). Managing nitrogen for sustainable development. Nature *528*, 51. 10.1038/nature15743.
103. Alexander, P., Prestele, R., Verburg, P.H., Arneth, A., Baranzelli, C., Batista e Silva, F., Brown, C., Butler, A., Calvin, K., Dendoncker, N., et al. (2017). Assessing uncertainties in land cover projections. Glob. Chang. Biol. *23*, 767-781. doi:10.1111/gcb.13447.
104. Gustavsson, J., Cederberg, C., Sonnesson, U., van Otterdijk, R., and Meybeck, A. (2011). Global Food Losses and Food Waste: Extent, Causes and Prevention. Food and Agriculture Organization of the United Nations.
105. FAOSTAT (2017). Food Balances (old methodology and population). Food and Agriculture Organization of the United Nations. 01 March 2020. http://faostat.fao.org/default.aspx.
106. Davis, K.F., Gephart, J.A., Emery, K.A., Leach, A.M., Galloway, J.N., and D'Odorico, P. (2016). Meeting future food demand with current agricultural resources. Glob. Environ. Chang. *39*, 125-132. http://dx.doi.org/10.1016/j.gloenvcha.2016.05.004.
107. Weindl, I., Popp, A., Bodirsky, B.L., Rolinski, S., Lotze-Campen, H., Biewald, A., Humpenöder, F., Dietrich, J.P., and Stevanović, M. (2017). Livestock and human use of land: Productivity trends and dietary choices as drivers of future land and carbon dynamics. Glob. Planet Chang *159*, 1-10. https://doi.org/10.1016/j.gloplacha.2017.10.002.
108. Weindl, I., Bodirsky, B.L., Rolinski, S., Biewald, A., Lotze-Campen, H., Müller, C., Dietrich, J.P., Humpenöder, F., Stevanović, M., Schaphoff, S., and Popp, A. (2017). Livestock production and the water challenge of future food supply: Implications of agricultural management and dietary choices. Glob. Environ. Chang. *47*, 121-132. https://doi.org/10.1016/j.gloenvcha.2017.09.010.
109. de Fraiture, C., and Wichelns, D. (2010). Satisfying future water demands for agriculture. Agric. Water Manage. *97*, 502-511. https://doi.org/10.1016/j.agwat.2009.08.008.
110. Tilman, D., Balzer, C., Hill, J., and Befort, B.L. (2011). Global food demand and the sustainable intensification of agriculture. Proc. Natl. Acad. Sci. U.S.A. *108*, 20260-20264. 10.1073/pnas.1116437108.
111. Mogollón, J.M., Beusen, A.H.W., van Grinsven, H.J.M., Westhoek, H., and Bouwman, A.F. (2018). Future agricultural phosphorus demand according to the shared socioeconomic pathways. Glob. Environ. Chang. *50*, 149-163. https://doi.org/10.1016/j.gloenvcha.2018.03.007.
112. Doelman, J.C., Stehfest, E., Tabeau, A., van Meijl, H., Lassaletta, L., Gernaat, D.E.H.J., Hermans, K., Harmsen, M., Daioglou, V., Biemans, H., et al. (2018). Exploring SSP land-use dynamics using the IMAGE model: Regional and gridded scenarios of land-use change and land-based climate change mitigation. Glob. Environ. Chang. *48*, 119-135. https://doi.org/10.1016/j.gloenvcha.2017.11.014.
113. Beusen, A.H.W., Doelman, J.C., Van Beek, L.P.H., Van Puijenbroek, P.J.T.M., Mogollón, J.M., Van Grinsven, H.J.M., Stehfest, E., Van Vuuren, D.P., and Bouwman, A.F. (2022). Exploring river nitrogen and phosphorus loading and export to global coastal waters in the Shared Socio-economic pathways. Glob. Environ. Chang. *72*, 102426. https://doi.org/10.1016/j.gloenvcha.2021.102426.
114. FAO (2018). The Future of Food and Agricutlure: Alternative Pathways to 2050. United Nations Food and Agriculture Organization.
115. Doelman, J.C., Beier, F.D., Stehfest, E., Bodirsky, B.L., Beusen, A.H.W., Humpenöder, F., Mishra, A., Popp, A., van Vuuren, D.P., de Vos, L., et al. (2022). Quantifying synergies and trade-offs in the global water-land-food-climate nexus using a multi-model scenario approach. Environ. Res. Lett. *17*, 045004. 10.1088/1748-9326/ac5766.
116. Van Vuuren, D., Stehfest, E., Gernaat, D., de Boer, H.-S., Daioglou, V., Doelman, J., Edelenbosch, O., Harmsen, M., van Zeist, W.-J., and van den Berg, M. (2021). The 2021 SSP scenarios of the IMAGE 3.2 model. PBL Netherlands Environmental Assessment Agency. https://www.pbl.nl/en/publications/the-2021-ssp-scenarios-of-the-image-32-model.
117. CIRAD (2016). Agrimonde-Terra: Foresight land use and food security in 2050. INRA/CIRAD.
118. Tubiello, F.N., Rosenzweig, C., Conchedda, G., Karl, K., Gütschow, J., Xueyao, P., Obli-Laryea, G., Wanner, N., Qiu, S.Y., Barros, J.D., et al. (2021). Greenhouse gas emissions from food systems: building the evidence base. Environ. Res. Lett. *16*, 065007. 10.1088/1748-9326/ac018e.
119. Tubiello, F.N., Karl, K., Flammini, A., Gütschow, J., Obli-Laryea, G., Conchedda, G., Pan, X., Qi, S.Y., Halldórudóttir Heiðarsdóttir, H., Wanner, N., et al. (2022). Pre- and post-production processes increasingly dominate greenhouse gas emissions from agri-food systems. Earth Syst. Sci. Data *14*, 1795-1809. 10.5194/essd-14-1795-2022.
120. IPCC (2021). Summary for Policymakers. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on

Climate Change, V. Masson-Delmotte, P. Zhai, S.L. A. Pirani, C. Connors, S.B. Péan, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, et al., eds. (Intergovernmental Panel on Climate Change).
121. Bodirsky, B.L., Chen, D.M.-C., Weindl, I., Soergel, B., Beier, F., Molina Bacca, E.J., Gaupp, F., Popp, A., and Lotze-Campen, H. (2022). Integrating degrowth and efficiency perspectives enables an emission-neutral food system by 2100. Nat. Food. 10.1038/s43016-022-00500-3.
122. Hunter, M.C., Smith, R.G., Schipanski, M.E., Atwood, L.W., and Mortensen, D.A. (2017). Agriculture in 2050: Recalibrating Targets for Sustainable Intensification. Bioscience *67*, 385-390. 10.1093/biosci/bix010.
123. Pretty, J. (2018). Intensification for redesigned and sustainable agricultural systems. Science *362*, eaav0294. 10.1126/science.aav0294.
124. Morais, T.G., Teixeira, R.F.M., Lauk, C., Theurl, M.C., Winiwarter, W., Mayer, A., Kaufmann, L., Haberl, H., Domingos, T., and Erb, K.H. (2021). Agroecological measures and circular economy strategies to ensure sufficient nitrogen for sustainable farming. Glob. Environ. Chang. *69*, 102313. https://doi.org/10.1016/j.gloenvcha.2021.102313.
125. Pikaar, I., Matassa, S., Bodirsky, B.L., Weindl, I., Humpenöder, F., Rabaey, K., Boon, N., Bruschi, M., Yuan, Z., van Zanten, H., et al. (2018). Decoupling Livestock from Land Use through Industrial Feed Production Pathways. Environ. Sci. Techno. *52*, 7351-7359. 10.1021/acs.est.8b00216.
126. Van Zanten, H.H.E., Van Ittersum, M.K., and De Boer, I.J.M. (2019). The role of farm animals in a circular food system. Glob. Food Sec. *21*, 18-22. https://doi.org/10.1016/j.gfs.2019.06.003.
127. van Selm, B., Hijbeek, R., van Middelaar, C.E., de Boer, I.J.M., and van Ittersum, M.K. (2025). How to use residual biomass streams in circular food systems to minimise land use or GHG emissions. Agric. Syst. *222*, 104185. https://doi.org/10.1016/j.agsy.2024.104185.
128. Humpenöder, F., Popp, A., Merfort, L., Luderer, G., Weindl, I., Bodirsky, B.L., Stevanović, M., Klein, D., Rodrigues, R., Bauer, N., et al. (2024). Food matters: Dietary shifts increase the feasibility of 1.5°C pathways in line with the Paris Agreement. Sci. Adv. *10*, eadj3832. doi:10.1126/sciadv.adj3832.
129. Parodi, A., Leip, A., De Boer, I.J.M., Slegers, P.M., Ziegler, F., Temme, E.H.M., Herrero, M., Tuomisto, H., Valin, H., Van Middelaar, C.E., et al. (2018). The potential of future foods for sustainable and healthy diets. Nat. Sustain. *1*, 782-789. 10.1038/s41893-018-0189-7.
130. Herrero, M., Thornton, P.K., Mason-D'Croz, D., Palmer, J., Benton, T.G., Bodirsky, B.L., Bogard, J.R., Hall, A., Lee, B., Nyborg, K., et al. (2020). Innovation can accelerate the transition towards a sustainable food system. Nat. Food *1*, 266-272. 10.1038/s43016-020-0074-1.
131. Humpenöder, F., Bodirsky, B.L., Weindl, I., Lotze-Campen, H., Linder, T., and Popp, A. (2022). Projected environmental benefits of replacing beef with microbial protein. Nature *605*, 90-96. 10.1038/s41586-022-04629-w.
132. McGreevy, S.R., Rupprecht, C.D.D., Niles, D., Wiek, A., Carolan, M., Kallis, G., Kantamaturapoj, K., Mangnus, A., Jehlička, P., Taherzadeh, O., et al. (2022). Sustainable agrifood systems for a post-growth world. Nat. Sustain. 10.1038/s41893-022-00933-5.
133. Herrero, M., Havlík, P., Valin, H., Notenbaert, A., Rufino, M.C., Thornton, P.K., Blümmel, M., Weiss, F., Grace, D., and Obersteiner, M. (2013). Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. Proc. Natl. Acad. Sci. U.S.A. *110*, 20888-20893. 10.1073/pnas.1308149110.
134. Zanten, H.H.E.V., Mario, H., Ollie, V.H., Elin, R., Adrian, M., Tara, G., J., G.P., Christian, S., and M., D.B.I.J. (2018). Defining a land boundary for sustainable livestock consumption. Glob. Chang. Biol. *24*, 4185–4194. doi:10.1111/gcb.14321.
135. Ehrlich, P. (2021). Why no mention of overpopulation in talk of food systems? Nat. Food *598*, 257.
136. Crist, E., Mora, C., and Engelman, R. (2017). The interaction of human population, food production, and biodiversity protection. Science *356*, 260-264. 10.1126/science.aal2011.
137. Crane-Droesch, A., Abiven, S., Jeffery, S., and Torn, M.S. (2013). Heterogeneous global crop yield response to biochar: a meta-regression analysis. Environ. Res. Lett. *8*, 044049. 10.1088/1748-9326/8/4/044049.
138. Steward, P.R., Dougill, A.J., Thierfelder, C., Pittelkow, C.M., Stringer, L.C., Kudzala, M., and Shackelford, G.E. (2018). The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: A meta-regression of yields. Agric. Ecosyst. Environ. *251*, 194-202. https://doi.org/10.1016/j.agee.2017.09.019.
139. Lori, M., Symnaczik, S., Mäder, P., De Deyn, G., and Gattinger, A. (2017). Organic farming enhances soil microbial abundance and activity—A meta-analysis and meta-regression. PLoS ONE *12*, e0180442. 10.1371/journal.pone.0180442.
140. Fan, D., He, W., Smith, W.N., Drury, C.F., Jiang, R., Grant, B.B., Shi, Y., Song, D., Chen, Y., Wang, X., et al. (2022). Global evaluation of inhibitor impacts on ammonia and nitrous oxide emissions from

agricultural soils: A meta-analysis. Glob. Chang. Biol. *28*, 5121-5141. https://doi.org/10.1111/gcb.16294.
141. Flies, E.J., Brook, B.W., Blomqvist, L., and Buettel, J.C. (2018). Forecasting future global food demand: A systematic review and meta-analysis of model complexity. Environ. Int. *120*, 93-103. https://doi.org/10.1016/j.envint.2018.07.019.
142. Tredennick, A.T., Hooker, G., Ellner, S.P., and Adler, P.B. (2021). A practical guide to selecting models for exploration, inference, and prediction in ecology. Ecology *102*, e03336. https://doi.org/10.1002/ecy.3336.
143. Rodriguez, J.D., Perez, A., and Lozano, J.A. (2010). Sensitivity Analysis of k-Fold Cross Validation in Prediction Error Estimation. IEEE Transactions on Pattern Analysis and Machine Intelligence *32*, 569-575. 10.1109/TPAMI.2009.187.
144. Bell, A., Fairbrother, M., and Jones, K. (2019). Fixed and random effects models: making an informed choice. Quality & Quantity *53*, 1051-1074. 10.1007/s11135-018-0802-x.
145. Harrison, X.A., Donaldson, L., Correa-Cano, M.E., Evans, J., Fisher, D.N., Goodwin, C.E.D., Robinson, B.S., Hodgson, D.J., and Inger, R. (2018). A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ *6*, e4794-e4794. 10.7717/peerj.4794.
146. Diniz Oliveira, T., Brunelle, T., Guenet, B., Ciais, P., Leblanc, F., and Guivarch, C. (2021). A mixed-effect model approach for assessing land-based mitigation in integrated assessment models: A regional perspective. Glob. Chang. Biol. *27*, 4671-4685. https://doi.org/10.1111/gcb.15738.
147. Knowles, J.E., Frederick, C., and Whitwirth, A. (2020). merTools: Tools for Analyzing Mixed Effect Regression Models}.
148. Lemons, D.S. (2002). An Introduction to Stochastic Processes in Physics (The Johns Hopkins University Press).
149. Stehfest, E., van Zeist, W.-J., Valin, H., Havlik, P., Popp, A., Kyle, P., Tabeau, A., Mason-D'Croz, D., Hasegawa, T., Bodirsky, B.L., et al. (2019). Key determinants of global land-use projections. Nat. Commun. *10*, 2166. 10.1038/s41467-019-09945-w.
150. Schleussner, C.-F., Ganti, G., Rogelj, J., and Gidden, M.J. (2022). An emission pathway classification reflecting the Paris Agreement climate objectives. Commun. Earth Environ. *3*, 135. 10.1038/s43247-022-00467-w.
151. Mastrandrea, M.D., C.B. Field, T.F. Stocker, O. Edenhofer, K.L. Ebi, D.J. Frame, H. Held, E. Kriegler, K.J. Mach,, and P.R. Matschoss, G.-K.P., G.W. Yohe, F.W. Zwiers (2010). Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties. Intergovernmental Panel on Climate Change (IPCC). Available at: https://www.ipcc.ch/site/assets/uploads/2018/05/uncertainty-guidance-note.pdf.
152. Kc, S., and Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. Glob. Environ. Chang. *42*, 181-192. https://doi.org/10.1016/j.gloenvcha.2014.06.004.
153. UN DESA (2024). World Population Prospects 2024: Summary of Results (UN DESA/POP/2024/TR/NO. 9). United Nations Department of Economic and Social Affairs, Population Division.
154. WIC, I. (2024). Population and Human Capital Projections - 2023. IIASA and Wittgenstein Center (WIC).
155. Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., et al. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Glob. Environ. Chang. *42*, 153-168. 10.1016/j.gloenvcha.2016.05.009.
156. Heck, V., Hoff, H., Wirsenius, S., Meyer, C., and Kreft, H. (2018). Land use options for staying within the Planetary Boundaries – Synergies and trade-offs between global and local sustainability goals. Glob. Environ. Chang. *49*, 73-84. https://doi.org/10.1016/j.gloenvcha.2018.02.004.
157. Bouwman, L., Goldewijk, K.K., Van Der Hoek, K.W., Beusen, A.H.W., Van Vuuren, D.P., Willems, J., Rufino, M.C., and Stehfest, E. (2013). Exploring global changes in nitrogen and phosphorus cycles in agriculture induced by livestock production over the 1900-2050 period. Proc. Natl. Acad. Sci. U.S.A. *110*, 20882-20887. http://dx.doi.org/10.1073/pnas.1012878108.
158. Wirsenius, S., Azar, C., and Berndes, G. (2010). How much land is needed for global food production under scenarios of dietary changes and livestock productivity increases in 2030? Agric. Syst. *103*, 621-638. http://dx.doi.org/10.1016/j.agsy.2010.07.005.
159. Pelletier, N., and Tyedmers, P. (2010). Forecasting potential global environmental costs of livestock production 2000-2050. Proc. Natl. Acad. Sci. U.S.A. *107*, 18371-18374. 10.1073/pnas.1004659107.

160. KC, K.B., Dias, G.M., Veeramani, A., Swanton, C.J., Fraser, D., Steinke, D., Lee, E., Wittman, H., Farber, J.M., Dunfield, K., et al. (2018). When too much isn't enough: Does current food production meet global nutritional needs? PLoS ONE *13*, e0205683. 10.1371/journal.pone.0205683.
161. Metson, G.S., Bennett, E.M., and Elser, J.J. (2012). The role of diet in phosphorus demand. Environ. Res. Lett. *7*, 044043. 10.1088/1748-9326/7/4/044043.
162. Odegard, I., and van der Voet, E. (2014). The future of food—Scenarios and the effect on natural resource use in agriculture in 2050. Ecol. Econ. *97*, 51-59.
163. Hiç, C., Pradhan, P., Rybski, D., and Kropp, J.P. (2016). Food Surplus and Its Climate Burdens. Environ. Sci. Techno. *50*, 4269-4277. 10.1021/acs.est.5b05088.
164. Green, R., Allen, L.H., Bjørke-Monsen, A.-L., Brito, A., Guéant, J.-L., Miller, J.W., Molloy, A.M., Nexo, E., Stabler, S., Toh, B.-H., et al. (2017). Vitamin B12 deficiency. Nature Reviews Disease Primers *3*, 17040. 10.1038/nrdp.2017.40.
165. USDA (2016). Nutrient Data Laboratory. USDA National Nutrient Database for Standard Reference, Release 28 (Slightly revised). Version Current: May 2016. US Department of Agriculture, Agricultural Research Service.
166. WHO. (2004). Vitamin and mineral requirements in human nutrition, Second Edition (World Health Organization and Food and Agriculture Organization of the United Nations).
167. EFSA NDA Panel (2015). Scientific Opinion on Dietary Reference Values for cobalamin (vitamin B12). EFSA Journal *13*, 4150. https://doi.org/10.2903/j.efsa.2015.4150.
168. Alexandratos, N., and Bruinsma, J. (2012). World agriculture towards 2030/2050: the 2012 revision. United Nations Food and Agriculture Organization.
169. Pradhan, P., Reusser, D.E., and Kropp, J.P. (2013). Embodied Greenhouse Gas Emissions in Diets. PLoS ONE *8*, e62228. 10.1371/journal.pone.0062228.
170. Damerau, K., Patt, A.G., and van Vliet, O.P.R. (2016). Water saving potentials and possible trade-offs for future food and energy supply. Glob. Environ. Chang. *39*, 15-25. http://dx.doi.org/10.1016/j.gloenvcha.2016.03.014.
171. Theurl, M.C., Lauk, C., Kalt, G., Mayer, A., Kaltenegger, K., Morais, T.G., Teixeira, R.F.M., Domingos, T., Winiwarter, W., Erb, K.-H., and Haberl, H. (2020). Food systems in a zero-deforestation world: Dietary change is more important than intensification for climate targets in 2050. Sci. Total Environ. *735*, 139353. https://doi.org/10.1016/j.scitotenv.2020.139353.
172. Kearney, J. (2010). Food consumption trends and drivers. Philos. Trans. R. Soc. Lond., B, Biol. Sci. *365*, 2793-2807.
173. Bodirsky, B.L., Popp, A., Lotze-Campen, H., Dietrich, J.P., Rolinski, S., Weindl, I., Schmitz, C., Müller, C., Bonsch, M., Humpenöder, F., et al. (2014). Reactive nitrogen requirements to feed the world in 2050 and potential to mitigate nitrogen pollution. Nat. Commun. *5*, 3858. 10.1038/ncomms4858.
174. Gatto, A., and Chepeliev, M. (2024). Global food loss and waste estimates show increasing nutritional and environmental pressures. Nat. Food. 10.1038/s43016-023-00915-6.
175. Lopez Barrera, E., and Hertel, T. (2021). Global food waste across the income spectrum: Implications for food prices, production and resource use. Food Policy *98*, 101874. https://doi.org/10.1016/j.foodpol.2020.101874.
176. Salemdeeb, R., Font Vivanco, D., Al-Tabbaa, A., and zu Ermgassen, E.K.H.J. (2017). A holistic approach to the environmental evaluation of food waste prevention. Waste Management *59*, 442-450. https://doi.org/10.1016/j.wasman.2016.09.042.
177. Reynolds, C., Goucher, L., Quested, T., Bromley, S., Gillick, S., Wells, V.K., Evans, D., Koh, L., Carlsson Kanyama, A., Katzeff, C., et al. (2019). Review: Consumption-stage food waste reduction interventions – What works and how to design better interventions. Food Policy. https://doi.org/10.1016/j.foodpol.2019.01.009.
178. UNEP (2021). Food Waste Index Report 2021. United Nations Environment Programme, . https://www.unep.org/resources/report/unep-food-waste-index-report-2021.
179. Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., and Foley, J.A. (2012). Closing yield gaps through nutrient and water management. Nature *490*, 254. 10.1038/nature11420.
180. Lobell, D.B., Cassman, K.G., and Field, C.B. (2009). Crop Yield Gaps: Their Importance, Magnitudes, and Causes. Annu. Rev. Environ. Resour. *34*, 179-204. 10.1146/annurev.environ.041008.093740.
181. Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O/'Connell, C., Ray, D.K., West, P.C., et al. (2011). Solutions for a cultivated planet. Nature *478*, 337-342. http://dx.doi.org/10.1038/nature10452.
182. West, P.C., Gerber, J.S., Engstrom, P.M., Mueller, N.D., Brauman, K.A., Carlson, K.M., Cassidy, E.S., Johnston, M., MacDonald, G.K., Ray, D.K., and Siebert, S. (2014). Leverage points for improving global food security and the environment. Science *345*, 325-328. 10.1126/science.1246067.

183. Valin, H., Havlík, P., Mosnier, A., Herrero, M., Schmid, E., and Obersteiner, M. (2013). Agricultural productivity and greenhouse gas emissions: trade-offs or synergies between mitigation and food security? Environ. Res. Lett. *8*, 035019.
184. van Zeist, W.-J., Stehfest, E., Doelman, J.C., Valin, H., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Humpenöder, F., Kyle, P., et al. (2020). Are scenario projections overly optimistic about future yield progress? Glob. Environ. Chang. *64*, 102120. https://doi.org/10.1016/j.gloenvcha.2020.102120.
185. FAOSTAT (2024). Cereal yields (1961-2022).
186. Dietrich, J.P., Schmitz, C., Lotze-Campen, H., Popp, A., and Müller, C. (2014). Forecasting technological change in agriculture—An endogenous implementation in a global land use model. Technol. Forecast. Soc. Change *81*, 236-249. https://doi.org/10.1016/j.techfore.2013.02.003.
187. Jägermeyr, J., Müller, C., Ruane, A.C., Elliott, J., Balkovic, J., Castillo, O., Faye, B., Foster, I., Folberth, C., Franke, J.A., et al. (2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nat. Food. 10.1038/s43016-021-00400-y.
188. Thornton, P.K. (2010). Livestock production: recent trends, future prospects. Philos. Trans. R. Soc. Lond., B, Biol. Sci. *365*, 2853-2867. doi:10.1098/rstb.2010.0134.
189. Herrero, M., and Thornton, P.K. (2013). Livestock and global change: Emerging issues for sustainable food systems. Proc. Natl. Acad. Sci. U.S.A. *110*, 20878-20881. 10.1073/pnas.1321844111.
190. Davis, K.F., and D'Odorico, P. (2015). Livestock intensification and the influence of dietary change: A calorie-based assessment of competition for crop production. Sci. Total Environ. *538*, 817-823. https://doi.org/10.1016/j.scitotenv.2015.08.126.
191. Gerber, P., Vellinga, T., Opio, C., and Steinfeld, H. (2011). Productivity gains and greenhouse gas emissions intensity in dairy systems. Livest. Sci. *139*, 100-108. https://doi.org/10.1016/j.livsci.2011.03.012.
192. Arndt, C., Hristov, A.N., Price, W.J., McClelland, S.C., Pelaez, A.M., Cueva, S.F., Oh, J., Dijkstra, J., Bannink, A., Bayat, A.R., et al. (2022). Full adoption of the most effective strategies to mitigate methane emissions by ruminants can help meet the 1.5 °C target by 2030 but not 2050. Proc. Natl. Acad. Sci. U.S.A. *119*, e2111294119. doi:10.1073/pnas.2111294119.
193. Ridoutt, B., and Navarro Garcia, J. (2020). Cropland footprints from the perspective of productive land scarcity, malnutrition-related health impacts and biodiversity loss. J. Clean. Prod. *260*, 121150. https://doi.org/10.1016/j.jclepro.2020.121150.
194. Bouwman, A.F., Van der Hoek, K.W., Eickhout, B., and Soenario, I. (2005). Exploring changes in world ruminant production systems. Agric. Syst. *84*, 121-153. https://doi.org/10.1016/j.agsy.2004.05.006.
195. Gephart, J.A., Henriksson, P.J.G., Parker, R.W.R., Shepon, A., Gorospe, K.D., Bergman, K., Eshel, G., Golden, C.D., Halpern, B.S., Hornborg, S., et al. (2021). Environmental performance of blue foods. Nature *597*, 360-365. 10.1038/s41586-021-03889-2.
196. Erb, K.-H., Lauk, C., Kastner, T., Mayer, A., Theurl, M.C., and Haberl, H. (2016). Exploring the biophysical option space for feeding the world without deforestation. Nat. Commun. *7*, 11382. 10.1038/ncomms11382.
197. van Selm, B., Frehner, A., de Boer, I.J.M., van Hal, O., Hijbeek, R., van Ittersum, M.K., Talsma, E.F., Lesschen, J.P., Hendriks, C.M.J., Herrero, M., and van Zanten, H.H.E. (2022). Circularity in animal production requires a change in the EAT-Lancet diet in Europe. Nat. Food *3*, 66-73. 10.1038/s43016-021-00425-3.
198. Lassaletta, L., Billen, G., Garnier, J., Bouwman, L., Velazquez, E., Mueller, N.D., and Gerber, J.S. (2016). Nitrogen use in the global food system: past trends and future trajectories of agronomic performance, pollution, trade, and dietary demand. Environ. Res. Lett. *11*, 095007.
199. Powell, T.W.R., and Lenton, T.M. (2012). Future carbon dioxide removal via biomass energy constrained by agricultural efficiency and dietary trends. Energy Environ. Sci. *5*, 8116-8133. 10.1039/C2EE21592F.
200. FAOSTAT (2021). FAOSTAT Commodity Balances - Crops Primary Equivalent. Food and Agriculture Organization of the United Nations.
201. Lucas, P.L., van Vuuren, D.P., Olivier, J.G.J., and den Elzen, M.G.J. (2007). Long-term reduction potential of non-CO2 greenhouse gases. Environ. Sci. Policy *10*, 85-103. https://doi.org/10.1016/j.envsci.2006.10.007.
202. Popp, A., Lotze-Campen, H., and Bodirsky, B. (2010). Food consumption, diet shifts and associated non-CO2 greenhouse gases from agricultural production. Glob. Environ. Chang. *20*, 451-462. https://doi.org/10.1016/j.gloenvcha.2010.02.001.
203. Frank, S., Havlík, P., Stehfest, E., van Meijl, H., Witzke, P., Pérez-Domínguez, I., van Dijk, M., Doelman, J.C., Fellmann, T., Koopman, J.F.L., et al. (2019). Agricultural non-CO2 emission reduction potential in the context of the 1.5 °C target. Nat. Clim. Chang. *9*, 66-72. 10.1038/s41558-018-0358-8.

204. Smith, P., Nayak, D., Linthorst, G., Peters, D., Bucquet, C., Vuuren, D.P.v., Stehfest, E., Harmsen, M., and Brink, L.v.d. (2016). Science-based GHG emissions targets for agriculture and forestry commodities. KR foundation/University of Aberdeen/PBL Netherlands Environmental Assessment Agency/Ecofys.
205. Smith, P., Davis, S.J., Creutzig, F., Fuss, S., Minx, J., Gabrielle, B., Kato, E., Jackson, R.B., Cowie, A., Kriegler, E., et al. (2016). Biophysical and economic limits to negative CO2 emissions. Nature Clim. Change *6*, 42-50. 10.1038/nclimate2870.
206. Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., et al. (2008). Greenhouse gas mitigation in agriculture. Philos. Trans. R. Soc. Lond., B, Biol. Sci. *363*, 789-813. 10.1098/rstb.2007.2184.
207. Harper, A.B., Powell, T., Cox, P.M., House, J., Huntingford, C., Lenton, T.M., Sitch, S., Burke, E., Chadburn, S.E., Collins, W.J., et al. (2018). Land-use emissions play a critical role in land-based mitigation for Paris climate targets. Nat. Commun. *9*, 2938. 10.1038/s41467-018-05340-z.
208. Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., and Tempio, G. (2013). Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities (Food and Agriculture Organization of the United Nations (FAO)).
209. Smith, P., Calvin, K., Nkem, J., Campbell, D., Cherubini, F., Grassi, G., Korotkov, V., Le Hoang, A., Lwasa, S., McElwee, P., et al. (2020). Which practices co-deliver food security, climate change mitigation and adaptation, and combat land degradation and desertification? Glob. Chang. Biol. *26*, 1532-1575. https://doi.org/10.1111/gcb.14878.
210. Stehfest, E., Bouwman, L., van Vuuren, D.P., den Elzen, M.G.J., Eickhout, B., and Kabat, P. (2009). Climate benefits of changing diet. Clim. Chang. *95*, 83-102. 10.1007/s10584-008-9534-6.
211. Bennetzen, E.H., Smith, P., and Porter, J.R. (2016). Decoupling of greenhouse gas emissions from global agricultural production: 1970–2050. Glob. Chang. Biol. *22*, 763-781. 10.1111/gcb.13120.
212. Chang, J., Peng, S., Yin, Y., Ciais, P., Havlik, P., and Herrero, M. (2021). The Key Role of Production Efficiency Changes in Livestock Methane Emission Mitigation. AGU Advances *2*, e2021AV000391. https://doi.org/10.1029/2021AV000391.
213. World Bank (2024) – processed by Our World in Data (2024). Agricultural water as a share of total water withdrawals. In W.D.I. Food and Agriculture Organization of the United Nations (via World Bank), ed. Our World in Data.
214. Wallace, J.S. (2000). Increasing agricultural water use efficiency to meet future food production. Agric. Ecosyst. Environ. *82*, 105-119. https://doi.org/10.1016/S0167-8809(00)00220-6.
215. Grafton, R.Q., Williams, J., Perry, C.J., Molle, F., Ringler, C., Steduto, P., Udall, B., Wheeler, S.A., Wang, Y., Garrick, D., and Allen, R.G. (2018). The paradox of irrigation efficiency. Science *361*, 748-750. 10.1126/science.aat9314.
216. United Nations (2015). Transforming our World: The 2030 Agenda for Sustainable Development. United Nations.
217. UN Environment (2019). Global Environment Outlook – GEO-6: Healthy Planet, Healthy People. United Nations Environment Programme.
218. Hoekstra, A.Y., and Mekonnen, M.M. (2012). The water footprint of humanity. Proc. Natl. Acad. Sci. U.S.A. *109*, 3232-3237. 10.1073/pnas.1109936109.
219. Bhattacharya, A. (2019). Chapter 3 - Water-Use Efficiency Under Changing Climatic Conditions. In Changing Climate and Resource Use Efficiency in Plants, A. Bhattacharya, ed. (Academic Press), pp. 111-180. https://doi.org/10.1016/B978-0-12-816209-5.00003-9.
220. Hoekstra, A.Y., and Wiedmann, T.O. (2014). Humanity's unsustainable environmental footprint. Science *344*, 1114-1117.
221. UN-Water (2018). Progress on Water-Use Efficiency – Global baseline for SDG indicator 6.4.1. UN-Water & Food and Agriculture Organization of the United Nations.
222. Pfister, S., Bayer, P., Koehler, A., and Hellweg, S. (2011). Projected water consumption in future global agriculture: Scenarios and related impacts. Sci. Total Environ. *409*, 4206-4216. http://dx.doi.org/10.1016/j.scitotenv.2011.07.019.
223. Davis, K.F., Rulli, M.C., Seveso, A., and D'Odorico, P. (2017). Increased food production and reduced water use through optimized crop distribution. Nat. Geosci. *10*, 919–924. 10.1038/s41561-017-0004-5.
224. Dalin, C., Konar, M., Hanasaki, N., Rinaldo, A., and Rodriguez-Iturbe, I. (2012). Evolution of the global virtual water trade network. Proc. Natl. Acad. Sci. U.S.A. *109*, 5989-5994. doi:10.1073/pnas.1203176109.
225. Liu, X., Klemeš, J.J., Varbanov, P.S., Čuček, L., and Qian, Y. (2017). Virtual carbon and water flows embodied in international trade: a review on consumption-based analysis. J. Clean. Prod. *146*, 20-28. https://doi.org/10.1016/j.jclepro.2016.03.129.

226. Sutton, M.A., Bleeker, A., Howard, C., Bekunda, M., Grizzetti, B., De Vries, W., Van Grinsven, H., Abrol, Y., Adhya, T., Billen, G., et al. (2013). Our Nutrient World: The challenge to produce more food and energy with less pollution (Global Overview of Nutrient Management. Centre for Ecology and Hydrology, Edinburgh on behalf of the Global Partnership on Nutrient Management and the International Nitrogen Initiative.).
227. Zhang, X., Zou, T., Lassaletta, L., Mueller, N.D., Tubiello, F.N., Lisk, M.D., Lu, C., Conant, R.T., Dorich, C.D., Gerber, J., et al. (2021). Quantification of global and national nitrogen budgets for crop production. Nat. Food *2*, 529-540. 10.1038/s43016-021-00318-5.
228. Bouwman, A.F., Beusen, A.H.W., and Billen, G. (2009). Human alteration of the global nitrogen and phosphorus soil balances for the period 1970–2050. Global Biogeochem. Cycles *23*. doi:10.1029/2009GB003576.
229. Bodirsky, B.L., Popp, A., Weindl, I., Dietrich, J.P., Rolinski, S., Scheiffele, L., Schmitz, C., and Lotze-Campen, H. (2012). N2O emissions from the global agricultural nitrogen cycle – current state and future scenarios. Biogeosciences *9*, 4169-4197. 10.5194/bg-9-4169-2012.
230. van Vuuren, D.P., Kok, M., Esch, S., Jeuken, M., Lucas, P., Prins, A., Alkemade, R., Berg, M., Biermann, F., Grijp, N., et al. (2012). Roads from Rio+20: Pathways to achieve global sustainability goals by 2050. Netherlands Environmental Assessment Agency PBL.
231. Mogollón, J.M., Lassaletta, L., Beusen, A., Van Grinsven, H., Westhoek, H., and Bouwman, L.F.L. (2018). Assessing future reactive nitrogen inputs into global croplands based on the shared socioeconomic pathways. Environ. Res. Lett., DOI: 10.1088/1748-9326/aab1212. https://doi.org/10.1088/1748-9326/aab212.
232. Bowles, T.M., Atallah, S.S., Campbell, E.E., Gaudin, A.C.M., Wieder, W.R., and Grandy, A.S. (2018). Addressing agricultural nitrogen losses in a changing climate. Nat. Sustain. *1*, 399-408. 10.1038/s41893-018-0106-0.
233. Cordell, D., and White, S. (2014). Life's Bottleneck: Sustaining the World's Phosphorus for a Food Secure Future. Annu. Rev. Environ. Resour. *39*, 161-188. 10.1146/annurev-environ-010213-113300.
234. Willer, H., and Lernoud, J. (2019). The World of Organic Agriculture. Statistics and Emerging Trends 2019. Research Institute of Organic Agriculture (FiBL), Frick, and IFOAM - Organics International.
235. Alcamo, J., van Vuuren, D., Ringler, C., Cramer, W., Masui, T., Alder, J., and Schulze, K. (2005). Changes in Nature’s Balance Sheet: Model-based Estimates of Future Worldwide Ecosystem Services. Ecol. Soc. *10*, 19. 10.5751/ES-01551-100219.
236. Pretty, J., Benton, T.G., Bharucha, Z.P., Dicks, L.V., Flora, C.B., Godfray, H.C.J., Goulson, D., Hartley, S., Lampkin, N., Morris, C., et al. (2018). Global assessment of agricultural system redesign for sustainable intensification. Nat. Sustain. *1*, 441-446. 10.1038/s41893-018-0114-0.
237. Godfray, H.C.J., and Garnett, T. (2014). Food security and sustainable intensification. Philos. Trans. R. Soc. Lond., B, Biol. Sci. *369*. 10.1098/rstb.2012.0273.
238. Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., and Toulmin, C. (2010). Food security: the challenge of feeding 9 billion people. Science *327*, 812-818.
239. Laird, N.M., and Ware, J.H. (1982). Random-Effects Models for Longitudinal Data. Biometrics *38*, 963-974. 10.2307/2529876.
240. Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A., and Smith, G.M. (2009). Mixed Effects Modelling for Nested Data. In Mixed effects models and extensions in ecology with R, (Springer New York), pp. 101-142. 10.1007/978-0-387-87458-6_5.
241. Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting linear mixed-effects models using lme4. J. Stat. Softw. *67*, 1-48. 10.18637/jss.v067.i01.
242. Maas, C.J.M., and Hox, J.J. (2005). Sufficient Sample Sizes for Multilevel Modeling. Methodology: European Journal of Research Methods for the Behavioral and Social Sciences *1*, 86-92. 10.1027/1614-2241.1.3.86.
243. Snijders, T.A. (2005). Power and Sample Size in Multilevel Linear Models. In Encyclopedia of Statistics in Behavioral Science, B.S. Everitt, and D.C. Howell, eds. (John Wiley & Sons, Ltd), pp. 2208. doi:10.1002/0470013192.bsa492.
244. Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A., and Smith, G.M. (2009). Mixed effects models and extensions in ecology with R (Springer). 10.1007/978-0-387-87458-6_4.
245. Gelman, A., and Hill, J. (2007). Data Analysis Using Regression and Hierarchical/Multilevel Models (Cambridge University Press).
246. Barr, D.J., Levy, R., Scheepers, C., and Tily, H.J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. Journal of Memory and Language *68*, 255-278. https://doi.org/10.1016/j.jml.2012.11.001.

247. Matuschek, H., Kliegl, R., Vasishth, S., Baayen, H., and Bates, D. (2017). Balancing Type I error and power in linear mixed models. Journal of Memory and Language *94*, 305-315. https://doi.org/10.1016/j.jml.2017.01.001.
248. Minx, J.C., Lamb, W.F., Andrew, R.M., Canadell, J.G., Crippa, M., Döbbeling, N., Forster, P.M., Guizzardi, D., Olivier, J., Peters, G.P., et al. (2021). A comprehensive and synthetic dataset for global, regional, and national greenhouse gas emissions by sector 1970–2018 with an extension to 2019. Earth Syst. Sci. Data *13*, 5213-5252. 10.5194/essd-13-5213-2021.
249. Royston, P., Altman, D.G., and Sauerbrei, W. (2006). Dichotomizing continuous predictors in multiple regression: a bad idea. *25*, 127-141. doi:10.1002/sim.2331.
250. Dawson, N.V., and Weiss, R. (2012). Dichotomizing Continuous Variables in Statistical Analysis: A Practice to Avoid. Med. Decis. Making *32*, 225-226. 10.1177/0272989X12437605.
251. Delignette-Muller, M.L., and Dutang, C. (2015). fitdistrplus: An R Package for Fitting Distributions. 2015 *64*, 34. 10.18637/jss.v064.i04.
252. Fox, J., and Weisberg, S. (2019). An R Companion to Applied Regression, Third Edition (Sage).
253. Schielzeth, H. (2010). Simple means to improve the interpretability of regression coefficients. Methods Ecol. Evol. *1*, 103-113. 10.1111/j.2041-210X.2010.00012.x.
254. Olsen, L.R., Zachariae, H.B., Patil, I., and Lüdecke, D. (2022). cvms: Cross-Validation for Model Selection. R package version 1.3.7.
255. Fox, J., and Monette, G. (1992). Generalized Collinearity Diagnostics. Journal of the American Statistical Association *87*, 178-183. 10.2307/2290467.
256. R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing. R Foundation for Statistical Computing.
257. Koller, M. (2016). robustlmm: An R Package for Robust Estimation of Linear Mixed-Effects Models. J. Stat. Softw. *75*, 1 - 24. 10.18637/jss.v075.i06.
258. Maaz, T.M., Sapkota, T.B., Eagle, A.J., Kantar, M.B., Bruulsema, T.W., and Majumdar, K. (2021). Meta-analysis of yield and nitrous oxide outcomes for nitrogen management in agriculture. Glob. Chang. Biol. *27*, 2343-2360. https://doi.org/10.1111/gcb.15588.
259. Schielzeth, H., Dingemanse, N.J., Nakagawa, S., Westneat, D.F., Allegue, H., Teplitsky, C., Réale, D., Dochtermann, N.A., Garamszegi, L.Z., and Araya-Ajoy, Y.G. (2020). Robustness of linear mixed-effects models to violations of distributional assumptions. Methods Ecol. Evol. *11*, 1141-1152. https://doi.org/10.1111/2041-210X.13434.
260. Tremblay, A., and Ransijn, J. (2020). LMERConvenienceFunctions: Model Selection and Post-hoc Analysis for (G)LMER Models. R package version 3.0. Statistics Canada & University of Copenhagen.
261. Sirami, C., Gross, N., Baillod, A.B., Bertrand, C., Carrié, R., Hass, A., Henckel, L., Miguet, P., Vuillot, C., Alignier, A., et al. (2019). Increasing crop heterogeneity enhances multitrophic diversity across agricultural regions. Proc. Natl. Acad. Sci. U.S.A. *116*, 16442-16447. doi:10.1073/pnas.1906419116.
262. Nakagawa, S., and Schielzeth, H. (2013). A general and simple method for obtaining R2 from generalized linear mixed-effects models. *4*, 133-142. doi:10.1111/j.2041-210x.2012.00261.x.
263. Barton, K. (2019). MuMIn: Multi-Model Inference. R package version 1.43.6.
264. Lüdecke, D. (2019). sjPlot: Data Visualization for Statistics in Social Science. R package version 2.6.3.
265. Wolodzko, T. (2018). extraDistr: Additional Univariate and Multivariate Distributions. R package version 1.8.10.
266. Mekonnen, M.M., and Hoekstra, A.Y. (2012). A Global Assessment of the Water Footprint of Farm Animal Products. Ecosystems *15*, 401-415. 10.1007/s10021-011-9517-8.
267. IPCC (2019). 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. IPCC. https://www.ipcc-nggip.iges.or.jp/.
268. Dangal, S.R.S., Tian, H., Xu, R., Chang, J., Canadell, J.G., Ciais, P., Pan, S., Yang, J., and Zhang, B. (2019). Global Nitrous Oxide Emissions From Pasturelands and Rangelands: Magnitude, Spatiotemporal Patterns, and Attribution. Global Biogeochem. Cycles *33*, 200-222. https://doi.org/10.1029/2018GB006091.
269. Hayek, M.N., and Garrett, R.D. (2018). Nationwide shift to grass-fed beef requires larger cattle population. Environ. Res. Lett. *13*, 084005. 10.1088/1748-9326/aad401.
270. Lüdecke, D. (2022). sjPlot: Data Visualization for Statistics in Social Science. R package version 2.8.12.
271. Gerten, D., Heck, V., Jägermeyr, J., Bodirsky, B.L., Fetzer, I., Jalava, M., Kummu, M., Lucht, W., Rockström, J., Schaphoff, S., and Schellnhuber, H.J. (2020). Feeding ten billion people is possible within four terrestrial planetary boundaries. Nat. Sustain. 10.1038/s41893-019-0465-1.
272. Häyhä, T., Lucas, P.L., van Vuuren, D.P., Cornell, S.E., and Hoff, H. (2016). From Planetary Boundaries to national fair shares of the global safe operating space — How can the scales be bridged? Glob. Environ. Chang. *40*, 60-72. https://doi.org/10.1016/j.gloenvcha.2016.06.008.

273. Li, M., Wiedmann, T., and Hadjikakou, M. (2019). Towards meaningful consumption-based planetary boundary indicators: The phosphorus exceedance footprint. Glob. Environ. Chang. *54*, 227-238. https://doi.org/10.1016/j.gloenvcha.2018.12.005.
274. Lucas, P.L., Wilting, H.C., Hof, A.F., and van Vuuren, D.P. (2020). Allocating planetary boundaries to large economies: Distributional consequences of alternative perspectives on distributive fairness. Glob. Environ. Chang. *60*, 102017. https://doi.org/10.1016/j.gloenvcha.2019.102017.
275. O'Neill, D.W., Fanning, A.L., Lamb, W.F., and Steinberger, J.K. (2018). A good life for all within planetary boundaries. Nat. Sustain. *1*, 88-95. 10.1038/s41893-018-0021-4.
276. Fujimori, S., Hasegawa, T., Krey, V., Riahi, K., Bertram, C., Bodirsky, B.L., Bosetti, V., Callen, J., Després, J., Doelman, J., et al. (2019). A multi-model assessment of food security implications of climate change mitigation. Nat. Sustain. *2*, 386-396. 10.1038/s41893-019-0286-2.
277. Newbold, T., Hudson, L.N., Arnell, A.P., Contu, S., De Palma, A., Ferrier, S., Hill, S.L.L., Hoskins, A.J., Lysenko, I., Phillips, H.R.P., et al. (2016). Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. Science *353*, 288-291. 10.1126/science.aaf2201.
278. Leclère, D., Obersteiner, M., Barrett, M., Butchart, S.H.M., Chaudhary, A., De Palma, A., DeClerck, F.A.J., Di Marco, M., Doelman, J.C., Dürauer, M., et al. (2020). Bending the curve of terrestrial biodiversity needs an integrated strategy. Nature *585*, 551-556. 10.1038/s41586-020-2705-y.
279. Gibson, L., Lee, T.M., Koh, L.P., Brook, B.W., Gardner, T.A., Barlow, J., Peres, C.A., Bradshaw, C.J.A., Laurance, W.F., Lovejoy, T.E., and Sodhi, N.S. (2011). Primary forests are irreplaceable for sustaining tropical biodiversity. Nature *478*, 378-381. 10.1038/nature10425.
280. Mace, G.M., Reyers, B., Alkemade, R., Biggs, R., Chapin, F.S., Cornell, S.E., Díaz, S., Jennings, S., Leadley, P., Mumby, P.J., et al. (2014). Approaches to defining a planetary boundary for biodiversity. Glob. Environ. Chang. *28*, 289-297. https://doi.org/10.1016/j.gloenvcha.2014.07.009.
281. Lade, S.J., Steffen, W., de Vries, W., Carpenter, S.R., Donges, J.F., Gerten, D., Hoff, H., Newbold, T., Richardson, K., and Rockström, J. (2019). Human impacts on planetary boundaries amplified by Earth system interactions. Nat. Sustain. *3*, 119-128. 10.1038/s41893-019-0454-4.
282. Tilman, D., Fargione, J., Wolff, B., D'Antonio, C., Dobson, A., Howarth, R., Schindler, D., Schlesinger, W.H., Simberloff, D., and Swackhamer, D. (2001). Forecasting Agriculturally Driven Global Environmental Change. Science *292*, 281-284. 10.1126/science.1057544.
283. Golub, A.A., Henderson, B.B., Hertel, T.W., Gerber, P.J., Rose, S.K., and Sohngen, B. (2012). Global climate policy impacts on livestock, land use, livelihoods, and food security. Proc. Natl. Acad. Sci. U.S.A., 201108772. 10.1073/pnas.1108772109.
284. Mueller, N.D., Lassaletta, L., Runck, B.C., Billen, G., Garnier, J., and Gerber, J.S. (2017). Declining spatial efficiency of global cropland nitrogen allocation. Global Biogeochem. Cycles *31*, 245-257. 10.1002/2016gb005515.
285. Latino, L.R., Pica-Ciamarra, U., and Wisser, D. (2020). Africa: The livestock revolution urbanizes. Glob. Food Sec. *26*, 100399. https://doi.org/10.1016/j.gfs.2020.100399.
286. Baldos, U.L.C., and Hertel, T.W. (2016). Debunking the 'new normal': Why world food prices are expected to resume their long run downward trend. Glob. Food Sec. *8*, 27-38. https://doi.org/10.1016/j.gfs.2016.03.002.
287. Eker, S., Reese, G., and Obersteiner, M. (2019). Modelling the drivers of a widespread shift to sustainable diets. Nat. Sustain. *2*, 725-735. 10.1038/s41893-019-0331-1.