The environmental costs and benefits of high-yield farming

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How we manage farming and food systems to meet rising demand is pivotal to the future of biodiversity. Extensive field data suggest impacts on wild populations would be greatly reduced through boosting yields on existing farmland so as to spare remaining natural habitats. High-yield farming raises other concerns because expressed per unit area it can generate high levels of externalities such as greenhouse gas (GHG) emissions and nutrient losses. However, such metrics underestimate the overall impacts of lower-yield systems, so here we develop a framework that instead compares externality and land costs per unit production. Applying this to diverse datasets describing the externalities of four major farm sectors reveals that, rather than involving trade-offs, the externality and land costs of alternative production systems can co-vary positively: per

unit production, land-efficient systems often produce lower externalities. For GHG emissions these associations become more strongly positive once forgone sequestration is included. Our conclusions are limited: remarkably few studies report externalities alongside yields; many important externalities and farming systems are not adequately measured; and realising the environmental benefits of high-yield systems typically requires additional measures to limit farmland expansion. However, applying our framework identifies several high yield/low externality systems, and more generally suggests that trade-offs among key cost metrics are not as ubiquitous as sometimes perceived.

Agriculture already covers around 40% of Earth's ice- and desert-free land and is responsible for around two-thirds of freshwater withdrawals[1]. Its immense scale means it is already the largest source of threat to other species[2], so how we cope with very marked increases in demand for farm products[3,4] will have profound consequences for the future of global biodiversity[2,5]. On the demand side, cutting food waste and excessive consumption of animal products are essential[1,5–8]. In terms of supply, farming at high yields (production per unit area) has considerable potential to restrict humanity's impacts on biodiversity. Detailed field data from five continents and almost 1800 species from birds to daisies[9–14] reveals so many depend on native vegetation that for most the impacts of agriculture on their populations would be best limited by farming at high yields (production per unit area) alongside sparing large tracts of intact habitat. Provided it can be coupled with setting aside (or restoring) natural habitats[15], lowering the land cost of agriculture thus appears central to addressing the extinction crisis[2].

However, a key counterargument against this land-sparing approach is that there are many other environmental costs of agriculture besides the biodiversity displaced by the land it requires, such as greenhouse gas (GHG) and ammonia emissions, soil erosion, eutrophication, dispersal of harmful pesticides, and freshwater depletion[5,7,16–18]. Measured per unit area of farmland the production of such externalities is sometimes greater in high- than lower-yield farming systems[17,18], potentially weakening the case for land sparing. But while expressing externalities per unit area can help identify local-scale impacts[19], it systematically underestimates the overall impact of lower-yield systems that occupy more land for the same level of production[20]. To be robust, assessments of externalities also need to include the off-site effects of management practices, such as crop production for supplementary feeding of livestock, or off-farm grazing for manure inputs to organic systems[20–22].

In this paper we argue that comparisons of the overall impacts of contrasting agricultural systems should focus on the sum of externality generated per unit of production[10] (paralleling measures of emissions intensity in climate-change analyses). This approach has for the most part only been adopted for a relatively narrow set of agricultural products[8,23] and farming systems (eg organic *vs* conventional, glasshouse *vs* open-field[20,24]). Here we develop a more general framework, and apply it to a diversity of data on some major farm sectors, farming systems and environmental externalities. Existing data are limited but nevertheless enable us to explore the utility of this new approach, test for broad patterns, and make an informed commentary on their significance for understanding the trade-offs and co-benefits of high- *vs* lower-yield systems.

Our framework involves compiling and plotting against one another (as in Fig. 1) the environmental costs of producing a given quantity of a commodity, across alternative production systems. We focus on examining variation in some better-known externality costs in relation to land cost (i.e. 1/yield), because of the latter's fundamental importance as a proxy for impacts on biodiversity. However, the approach could be used to explore associations among any other costs for which data are available. Comparisons must be made across production systems that could, in principle, be substituted for one another, so they must be measured or modelled identically and in the same place or, if not, potential confounding effects of different methods, climate and soils must be removed statistically.

If the idea that high-yield systems impose disproportionate externalities is true, we would expect plots of externality per unit production against land cost to show negative associations (Fig. 1a, blue symbols). However observed patterns may be more complex, and could reveal promising systems associated with low land cost and low externalities, or unpromising systems with high land and externality costs (Fig. 1b, green and red symbols respectively).

We assembled a team of sector and externality specialists to collate data for applying this framework to five major externalities (GHG emissions, water use, nitrogen [N], phosphorus [P] and soil losses) in four major sectors (Asian paddy rice, European wheat, Latin American beef, European dairy; Methods). We used both literature searches and consultation with experts to find paired yield and externality measurements for contrasting production systems in each sector. To be included, data had to be near-complete for a given externality – for example most major elements of GHG emissions or N losses had to be included, and if systems involved inputs (such as feeds or fertilisers) generated off-site we required data on the externality and land costs of their production. To limit confounding effects we narrowed our geographic scope within each sector (Supplementary Table 1), so that differences across systems could reasonably be attributed to farm practices rather than gross bioclimatic variation. Where co-products were generated we apportioned overall costs among products using economic allocation, but also investigated alternative allocation rules.

Our first key finding is that useable data are surprisingly scarce. Few studies measured paired externality and yield information, many reported externalities in substantially incomplete or irreconcilably divergent ways, and we could find no suitable data at all on some widely adopted practices. Nevertheless, we were able to obtain sufficient data to consider how externalities vary with land costs for nine out of 20 possible sector-externality combinations (Supplementary Table 1). The type of data available differed across these combinations (which we view as a useful test of the flexibility of our framework). For one combination the most extensive data we could find was from a long-term experiment at a single location. However because we were interested in generalities, where possible we used information from multiple studies – either field experiments or Life Cycle Assessments (LCAs) conducted across several sites – and used Generalised Linear Mixed Models (GLMMs) to correct for confounding method and site effects (Methods). Last, for two sectors we used process-based models parameterised for a fixed set of conditions representative of the region.

The data that we were able to obtain do not suggest that environmental costs are generally larger for farming systems with low land costs (i.e. high-yield systems; Fig. 2). If anything, positive associations – in which high-yield, land-efficient systems also have lower costs in other dimensions - appear more common. For Chinese paddy rice we found sufficient multi-site experimental data to explore how two focal externalities vary with land cost across contrasting systems (Methods). GHG costs (Fig. 2a) showed negative associations with land cost across monoculture and rotational systems (assessed separately). Our GLMMs revealed that for both system types, greater application of organic N lowered land cost but increased emissions (probably because of feedstock effects on the methanogenic community[25]; Supplementary Table 2); in contrast there was little or no GHG penalty from boosting yield using inorganic N (arrows, Fig. 2a). A large volume of data on rice and water use showed weakly positive covariation in costs (Fig. 2b). GLMMs indicated that increasing application of inorganic N boosted yield[26], and less irrigation lowered water use while incurring only a modest yield penalty[27] (Supplementary Table 2). Sensitivity tests of the rice analyses had little impact on these patterns (Methods; Supplementary Fig. 1).

We found two useable datasets on European wheat, both from the UK (Methods). Our GLMMS of data from a three-site experiment varying the N fertilisation regime revealed a complex relationship between GHG and land costs (Fig. 2c; Supplementary Table 2), driven by divergent responses[28] to adding ammonium nitrate (which lowers land costs but increases embodied GHG emissions) and adding urea (which lowers land costs without increasing GHG emissions per unit production, but at the cost of increased ammonia volatilisation). A single-site experiment varying inorganic N treatments showed a non-linear relationship between land cost and N losses (Fig. 2d), with increasing N application lowering both costs until an apparent threshold, beyond which land cost decreased further but at the cost of greater N leaching (see also ref. 1).

In livestock systems, all data we could find showed positive covariation between land costs and externalities. For Latin American beef, we located coupled yield estimates only for GHG emissions, but here two different types of data (Methods) revealed a common pattern. Using GLMMs again to control for potentially confounding study and site effects, we found that across multiple LCAs, pasture systems with greater land demands also generated greater emissions (Fig. 2e), with both land and GHG costs reduced by pasture improvements (using N fertilization or legumes). This pattern across contrasting pasture systems was confirmed by running RUMINANT[29] (Fig. 2f), a process-based model which also identified relatively low land and GHG costs for a series of silvopasture and feedlot-finishing systems (for which comparable LCA data were unavailable).

For European dairy, process-based modelling of three conventional and two organic systems, parameterised for the UK, enabled us to estimate four different externalities alongside yield (Methods). This showed that conventional systems – especially those using less grazing and more concentrates – had substantially lower land and also GHG costs (Fig. 2g), in part because concentrates reduce CH_4 emissions from fibre digestion[30]. Systems with greater use of concentrates (which have less rumen-degradable protein than grass[31]) also showed lower losses of N, P and soil per unit production (Fig. 2h,i,j). These broad patterns persisted when we used protein production rather than economic value to allocate costs to co-products (Methods; Supplementary Fig. 1).

As a final analysis we examined the additional externalities resulting from the different land requirements of contrasting systems. To generate the same quantity of agricultural product, low-yield systems require more land, allowing less to be retained or restored as natural habitat. This is in turn likely to increase GHG emissions and soil loss, and alter hydrology - though we could only find enough data to explore the first of these effects. For each sector we supplemented our direct GHG figures for each system with estimates of GHG consequences of their land use following IPCC methods[32] to calculate the sequestration potential of a hectare not used for farming and instead allowed to revert to climax vegetation (Methods). Results (Fig. 3) showed that these GHG opportunity costs of agriculture were typically greater than the emissions from farming activities themselves and, when added to them, in every sector generated strongly positive across-system associations between overall GHG cost and land cost. These patterns were maintained in sensitivity tests where we halved recovery rates or assumed half of the area potentially freed from farming was retained under agriculture (Methods; Supplementary Fig. 2). These findings thus confirm recent suggestions[33,34] that high-yield farming has the potential, provided land not needed for production is largely used for carbon sequestration, to make a substantial contribution to mitigating climate change.

This study was conceived as an exploration of whether high-yield systems – central to the idea of sparing land for nature in the face of enormous human demand for farm products - typically impose greater negative externalities than alternative approaches. Our results support three conclusions. First, useful data are worryingly limited. We considered only four relatively well-studied sectors and a narrow set of externalities - not including important impacts such as soil health or the effects of pesticide exposure on human health[20]. Even then we found studies reporting yield-linked estimates of externalities scarce, with many widely adopted or promising practices within these sectors undocumented. We were not able to examine complex agricultural systems (such as mixed farming, or agroforestry) which might have relatively low externalities. Relevant data on many significant developing-world farm sectors (such as cassava or dryland cereal production in Africa) also appear very limited. Given that a multi-dimensional understanding of the environmental effects of alternative production systems is integral to delivering sustainable intensification, more field measurements linking yield with a broader suite of externalities across a much wider range of practices and sectors are urgently needed.

Second, the available data on the sector-externality combinations we considered do not suggest that negative associations between land cost and other environmental costs of farming are typical (*cf* Fig. 1a). Many low-yield systems impose high costs in other ways too and, although certain yield-improving practices have undesirable impacts (e.g. organic fertilisation of paddy rice increasing CH_4 emissions; see also ref. 1), other practices appear capable of reducing several costs simultaneously (see also refs 1,8,24,35,36). High (but not excessive) application of inorganic N, for example, can lower land take of Chinese rice production without incurring GHG or water-use penalties. Similarly, in Brazilian beef production adopting better pasture management, semi-intensive silvopasture and feedlot-finishing can all boost yields alongside lowering GHG emissions. It is worth noting that although most systems we examined are relatively high-yielding, other recent work suggests that positive associations (*cf* trade-offs) among environmental and land costs may if anything be more likely in lower-yielding systems[1].

Third, pursuing promising high-yield systems is clearly not the same as encouraging business-as-usual industrial agriculture. Some high-yield practices we did not examine, such as the heavy use of pesticides in much tropical fruit cultivation[37], are likely to increase externality costs per unit production. Of the high-yield practices we did investigate some, such as applying fossil-fuel-derived ammonium nitrate to UK wheat, impose disproportionately high environmental costs. Others that seem favourable in terms of our focal externalities incur other costs, such as high NH_3 emissions from using urea on wheat[28], and management regimes that reduce costs in one geographic setting may not do so in others[1]. Much work characterising existing systems and designing new ones is thus needed. We suggest our framework can serve as a device for identifying existing yield-enhancing systems which also lower other environmental costs – and perhaps more importantly, for benchmarking the environmental performance of promising new technologies and practices.

We close by stressing that for high-yield systems to generate any environmental benefits they must be coupled with efforts to reduce rebound effects. Several plausible mechanisms for limiting these by explicitly linking yield growth to improved environmental performance have been identified – including strict land-use zoning; strategic deployment of yield-enhancing loans, expertise or infrastructure; conditional access to markets; and restructured rural subsidies[15]. Without such linkages, systems which perform well per unit production may nevertheless cause net environmental harm through higher profits or lower prices stimulating land conversion[38–40], and damage human health by encouraging overconsumption of cheap, calorie-rich but nutrient-deficient foods[41,42,]. If promising high-yield strategies are to help solve rather than exacerbate society's challenges, yield increases instead need to be combined with far-reaching demand-side interventions[1,6,41] and directly linked with effective measures to constrain agricultural expansion[15].

Methods

Focal sectors and externalities. We focused data-gathering on 4 globally significant farm sectors (Asian paddy rice, European wheat, Latin American beef, European dairy, accounting for 90%, 33%, 23% and 53% of global output of these products[43]) and 5 major externalities (greenhouse gas [GHG] emissions, water use, nitrogen [N], phosphorus [P] and soil losses). We chose these sector-externality combinations because preliminary work suggested they were relatively well-documented and had been quantified using a diversity of approaches (single-site experiments, multi-site experiments, Life Cycle Assessments [LCAs] and process-based models), enabling us to explore the generality of our framework. We then searched the literature and consulted experts to obtain paired yield and externality estimates of alternative production systems in each sector, narrowing our geographic scope so that differences in system performance could be reasonably attributed to management practices (rather than gross variation in bioclimate or soils). Our analyses have rarely been attempted previously and have complex data requirements, so we could not uniformly adopt standard search procedures developed for systematic reviews on topics where many published studies have attempted to answer the same research question.

This process generated data on ≥5 contrasting production systems for 9 out of 20 possible sector-externality combinations (Supplementary Table 1): Chinese rice-GHG emissions (from multi-site experiments); Chinese rice-water use (multi-site experiments); UK wheat-GHG emissions (a multi-site experiment); UK wheat-N emissions (a single-site experiment); Brazilian beef-GHG emissions (both LCA data and process-based models); and UK dairy-GHG emissions, and N, P and soil losses (using process-based models). Water use in the wheat and most of the beef systems examined was very limited and so not explored further. We were unable to find sufficient paired yield and externality estimates for the 9 remaining sector-externality combinations.

The land and externality costs of each system were then expressed as total area used per unit production (i.e. 1/yield) and total amount of externality generated per unit production. All estimates included the area used and externalities generated in producing externally-derived inputs (such as feed or fertilisers). For analytical tractability, as in other recent studies[1,24] we treat impacts occurring at different times and places as being additive. Occasional gaps in estimates for a system were filled using standard values from IPCC or other sources, or information from study authors or comparable systems (details below). Where experiments or LCAs were conducted at multiple sites, we built Generalised Linear Mixed Models (GLMMs) in the package lme4[44] in R version 3.3.1[45] to identify effects of specific management practices on land and externality cost estimates adjusted for potentially confounding biophysical and methodological effects. To illustrate the effects of statistically significant management variables (those whose 95% confidence intervals did not overlap zero; shown in bold in Supplementary Table 2) we estimated land and externality costs at the observed minimum and maximum values (for continuous management variables) or with the reference category and the category that showed the maximum effect size (for categorical variables), while keeping other variables constant; we then linked these points as arrows on our externality cost//land cost plots (Fig. 2 and Supplementary Fig. 1, with arrows displaced horizontally and/or vertically for increased visibility). Where systems generated significant co-products (wheat and rapeseed from rotational rice, beef from dairy) we allocated land and externality costs to the focal product in proportion to its relative contribution to the gross monetary value of production per unit area of farmland (from focal and co-product combined)[46].

Rice and GHG emissions. Systematic searching of Scopus for experimental studies that reported both yields and emissions of Chinese paddy rice systems identified 17 recently published studies[47–63] containing 140 paired yield-emissions estimates for different systems (after within-year replicates of a system were averaged). To limit confounding effects we analysed separately the data from monoculture systems from southern provinces (2 rice crops per year; 5 studies, 60 estimates) and rotational systems from more northerly provinces (1 rice and 1 wheat or rape crop per year; 12 studies, 80 estimates). The studies documented the effects of variation in the following practices: whether the land was tilled, the application rates of inorganic and organic N, and (for rotational systems only) the irrigation regime (continuous flooding *vs* episodic midseason drainage). There were insufficient data to examine the effects of seedling density, crop variety, organic practices, biochar application, use of groundcover to lower emissions, N fertiliser type, or K or P fertilisation.

Land cost estimates were expressed in ha-years/tonne rice grain (i.e. the inverse of annual production per hectare farmed). GHG costs were expressed in tonnes CO_2eq/tonne rice grain, and included CH_4 and N_2O emissions for growing seasons, CH_4 and N_2O emissions for fallow seasons (where necessary using mean values from refs 47–49,64), and embodied emissions from N fertiliser production (Yara emissions database; F. Brendrup, pers. comm.). We were unable to include emissions from producing manure or K or P fertiliser, or from farm machinery. For rotational systems we adjusted the land and GHG costs of rice production downwards by multiplying them by the proportional contribution of rice to the gross monetary value of production per unit area of farmland from rice and co-product combined (using mean post-2000 prices from ref. 43).

We next built GLMMs predicting variation in our estimates of land cost and GHG cost, for the monoculture and rotational datasets in turn. Management practices assessed as predictors were tillage regime (binary), the application rates of organic N and of inorganic N, and irrigation regime (binary; rotational systems only). Study site was included as a random effect. For all systems we adjusted for biophysical and methodological differences across sites using the first two components from a Principal Component Analysis of site scores for 14 variables: annual precipitation, precipitation during the driest and wettest quarters, annual mean temperature, mean temperatures during the warmest and coldest quarters, maximum temperature during the warmest month, mean monthly solar radiation, latitude, longitude, soil organic carbon content, plot size, replicates per estimate, and start year (with all climate data taken from refs 65,66). PCs 1 and 2 together explained 82.3% and 76.2% of the variance in these variables for monoculture and rotational systems, respectively. Soil pH and (soil pH)^2 were also assessed as additional predictors. For the monoculture models tolerance values were all >0.4 (indicating an absence of multicollinearity) except for the pH terms (both <0.1), which we therefore removed. For the rotational models all tolerance values indicated an absence of multicollinearity, but (soil pH)^2 was removed because AICc values indicated model fit was no better than using soil pH alone. Final models (Supplementary Table 2) were then used to plot site-adjusted land and GHG costs (as points) and statistically significant management effects (as arrows) in Fig. 2a. We also tested the effect of allocating land and GHG costs in rotational systems based on the relative energy content of rice and co-products[67] (*cf* relative contribution to gross monetary value; Supplementary Fig. 1).

We adopted similar though simpler approaches for the next two sector-externality combinations, which again used data from multi-site experiments.

Rice and water use. From a systematic search on Scopus we retrieved 15 recent studies[57,58,64,68–79] meeting our criteria which gave us 123 paired estimates describing the effects of variation in inorganic N application rate and irrigation regime on land and water costs of Chinese paddy rice. We analysed monoculture and rotational systems together but considered water use solely for periods of rice production. Land cost was expressed in ha-years/tonne rice grain, and water cost in m^3/tonne rice grain (excluding rainfall). We adjusted these estimates for site effects in GLMMs of variation in land and water costs using as predictors the application rate of inorganic N, and irrigation regime (a 6-level factor: continuous flooding, continuous flooding with drainage, alternate wetting and drying, controlled irrigation, mulches or plastic films, and long periods of dry soil), while accounting for the effect of study site as a random effect. Tolerance values were all >0.7. Final models (Supplementary

Table 2), were then used to plot site-adjusted land and water costs (as points) and significant management effects (as arrows) in Fig. 2b. Almost all sources reported data on only one rice season per year, but one study[68] included separate yield and water-use estimates for early- and late-season rice, so to check the robustness of our findings we re-ran the analysis with the early-season data from this study removed (Supplementary Fig. 1).

Wheat and GHG emissions. Experimental data for this analysis came from the Agricultural Greenhouse Gas Inventory Research Platform[80–83]. This provided 96 paired measures of variation in yield and N_2O emissions in response to changes in N fertiliser application rate and type; we expanded the emissions profile to include embodied emissions from N fertiliser production (from Yara emissions database; F. Brendrup, pers. comm.). We expressed land cost estimates in ha-years/tonne wheat (at 85% dry matter) and GHG cost estimates in tonnes CO_2eq/tonne wheat. Experiments were run in 3 regions, so to adjust for site effects we next built GLMMs of variation in land and GHG costs fitting study region as a random effect and using the application rates of ammonium nitrate, urea and dicyandiamide (a nitrification inhibitor) as predictors. Tolerance values were all >0.7. Adjusted land and GHG costs from the final models (Supplementary Table 2) are plotted in Fig. 2c, with arrows showing the significant effects of management practices.

Wheat and N losses. We assessed this sector-externality combination using data from a single study – Rothamsted's long-term Broadbalk wheat experiment, which investigates the effects of different inorganic N application rates on yields of winter wheat. During the 1990s changes in field drainage enabled the measurement (alongside yield) of plot-specific leaching losses of nitrate[84]. Mean land and N costs – expressed in ha-years/tonne wheat (at 85% dry matter) and kg N leached/tonne wheat, respectively – were averaged across the 8 seasons of available data (thus smoothing-out the substantial effects of interannual differences in rainfall), for each of 7 levels of application of N (ranging from 0-288 kg N [as ammonium nitrate] /ha-y; details in Fig. 2 legend). The results are plotted in Fig. 2d.

Beef and GHG emissions. Two types of data were available for this sector-externality combination, enabling us to compare findings across assessment techniques. First we examined all published LCAs of Brazilian beef production[85–92]. Supplementing this with a bioclimatically comparable dataset from tropical Mexico (R. Olea-Perez, pers. comm.) yielded 33 paired yield-emissions estimates for contrasting production systems. These varied in whether or not they used improved pasture, supplementary feeding, or improved breeds (which if unreported we inferred from age at first calving, and mortality and conception rates). There were insufficient LCA data to examine the effects of feedlots, silvopasture, or rotational grazing. Land cost estimates were calculated in ha-years/tonne Carcass Weight [CW], incorporating land used to grow feed, and assuming a dressing percentage of 50%[93]. GHG costs were derived in tonnes CO_2eq/tonne CW, including enteric CH_4 emissions, CH_4 and N_2O emissions from manure, N_2O emissions from managed pasture, emissions from supplementary feed production (where necessary using values from ref. 86), and embodied GHG emissions from N, P and K fertiliser production. There were too few data to include CO_2 emissions from lime application or farm machinery. Milk production was not a significant co-product. To control for site effects we then built GLMMs of variation in land and GHG costs using site as a random effect and use of improved pasture, supplementary feeding and improved breeds (each a binary factor) as predictors. Tolerance values were all >0.8. Adjusted land and GHG cost estimates from the final models (Supplementary Table 2) are plotted in Fig. 2e, with arrows describing the effects of significant management practices.

To complement this analysis we derived an equivalent GHG cost *vs* land cost plot (Fig. 2f) using a process-based model of beef production. RUMINANT[29] is an IPCC tier 3 digestion and metabolism model which uses stoichiometric equations to estimate production of meat, manure N and enteric methane for any given pasture quality, supplementary feed quantity and type, cattle breed, and region. We used plausible combinations of these settings (Supplementary Table 3) and corresponding values (provided by MH) of feed and forage protein, digestibility and carbohydrate content that were representative of the Brazilian beef sector to derive yield and emissions estimates for 86 contrasting pasture systems. To extend beyond the scope of the LCA analyses we also modelled 50 silvopasture systems by boosting feed quality to simulate access to *Leucaena*, and 8 feedlot-finishing systems by incorporating an 83-120 day feedlot phase when animals received high-quality mixed ration. For each system we included the whole herd, after determining the ratio of fattening:breeding animals using the DYNMOD demographic projection tool[94], based on system-specific reproductive performance parameters and animal growth rates (which reflected pasture quality and management; Supplementary Table 3). Breeding animals were kept under the same conditions as fattening animals except that in pasture and silvopasture systems they were not given supplementary feed. Stocking rates were set to sustainable carrying capacity for pasture and silvopasture, and 201 animals/ha for feedlots (DB pers. obs.). Yields were again converted to land cost in ha-years/tonne CW, including the area of feedlots and of land required to grow feed (using feed composition and yield data from refs 43,85). RUMINANT emissions estimates were supplemented with estimates of manure CH_4, CO_2 and N_2O emissions from feed production, and N_2O emissions from pasture fertilisation (from refs 32,85). Carbon sequestration by vegetation could not be included, which is likely to lead to a relative overestimate of GHG emissions from silvopasture[95]. All emissions were converted to CO_2eq units (using conversion factors from refs 32,85 and feedlot manure distribution from ref. 96) and expressed in tonnes CO_2eq/tonne CW.

Dairy and four externalities. The second set of process-based models we used enabled us to investigate how changes in GHG emissions, and N, P and soil losses varied with yield (and therefore land cost) across 5 dairy systems representative of UK farm practices (Supplementary Table 4; Figs.

2g-j). We modelled three conventional systems where animals had access to grazing for 270, 180 and 0 days/year, and two organic systems with grazing access for 270 and 200 days/year. Model farms were assigned rainfall and soil characteristics based on observed frequency distributions of these parameters for real farms of each type, with structural and management data (e.g. ratios of livestock categories and ages, N and P excretion rates) based on the models of refs 31,97,98. Manure management of each system used representative variations of the "manure management continuum"[99] (Supplementary Table 4). Physical performance data (annual milk yield, concentrate feed input, replacement rate and stocking rate) were obtained from the AHDB Dairy database (M. Topliff pers. comm.) for conventional systems and from DEFRA[100] for organic systems.

Yields were converted to land cost in ha-years/tonne Energy-Corrected Milk (ECM), including the area of land required to grow feed (from refs 101,102, with yield penalties for organic production from ref. 103). Because 57% of global beef production originates from the dairy sector[104], we then adjusted land costs downwards by multiplying them by the proportional contribution of milk to the gross monetary value of production per unit area of farmland from milk and beef combined (using milk and beef prices from the AHDB Dairy database (M. Topliff pers. comm.).

GHG cost estimates for each system comprised CH_4 emissions from enteric fermentation (based on ref. 31), CH_4 and N_2O emissions from manure management (following guidelines in refs 32 and 105), emissions from N fertiliser applications to pasture (from refs 106,107), and emissions from feed production (from ref. 108). Emissions from farm machinery and buildings were not included. All GHG emissions were then summed and expressed as an aggregate GHG emissions cost in tonnes CO_2eq/tonne ECM. Nitrate losses of each system were derived from the National Environment Agricultural Pollution–Nitrate (NEAP-N) model[109,110], whilst estimates of P and soil losses were based on the Phosphorus and Sediment Yield CHaracterisation In Catchments (PSYCHIC) model[111,98]. These last three costs were expressed in kg/tonne ECM. As with land costs, all externality costs were then downscaled by allocating a portion of them to the beef co-product of the systems, based on milk and beef prices. Finally, to test the sensitivity of our findings to this allocation rule, we also re-ran each analysis allocating costs to milk and beef using their relative protein content (from ref. 104) instead of relative contribution to gross monetary value (see Supplementary Fig. 1).

GHG opportunity costs of land farmed. Alongside the GHG emissions generated by agricultural activities themselves (analysed above), maintaining land under farming typically carries an additional GHG cost. Wherever the carbon content of farmed land is less than that of the natural habitat that could replace it if agriculture ceased, farming in effect imposes an opportunity cost of sequestration forgone[112], whose magnitude increases with the area under production (and hence with the land cost of the system). We quantified this GHG cost using the forgone sequestration method, whereby retaining the current land use is assumed to prevent the sequestration in soils and biomass that would occur if the land was allowed to revert to climax vegetation (see details in Supplementary Table 5).

For each forgone transition, values for annual accrual of biomass (≤20 years) were taken from Table 4.9 of ref. 32, assuming that the climax vegetation type for UK wheat and dairy was temperate oceanic forest (Europe), for Chinese rice it was tropical moist deciduous forest (Asia, continental), and for Brazilian beef it was tropical moist deciduous forest (South America). These annual accrual rates were assumed to persist over 20 years. The carbon content of all biomass was assumed to be 47% of dry matter (Table 4.3 of ref. 32).

Changes in soil carbon values were taken from the relevant mean percentage change in soil organic carbon values for each land conversion from the global meta-analysis of ref. 113. For UK wheat and

Chinese rice we used values for conversion of cropland to woodland. For UK dairy and Brazilian beef we used values for the conversion of grassland to woodland for the grazing land used by the livestock, and values for cropland to woodland for the land used to grow feed. Initial soil carbon values were taken from Table 2.3 of ref. 32. For UK wheat the soils were assumed to be "cold temperate, moist, high activity soils", for Chinese rice they were assumed to be "tropical, wet, low activity soils", for UK dairy the soils for grazing were assumed to be "cold temperate, moist, high activity soils" while the land used to grow imported feed was assumed to be "subtropical humid, LAC soils" (South America); for Brazilian beef the soils for both grazing and feed production were assumed to be "tropical, moist, low activity soils". In each case the relevant percentage change in soil organic carbon was applied to the initial soil carbon stock to calculate a change, which, following IPCC guidelines[32], we assumed to occur over 20 years.

Total annual forgone sequestration was then estimated by adding this annual change in soil organic carbon and the annual accrual of biomass carbon under reversion to climax vegetation. We assumed (as in ref. 34) that each 1ha reduction in land cost results in 1ha of recovering habitat. As above, our land cost estimates included any area needed to produce externally-derived inputs, and (for rotational rice and dairy) were adjusted downwards to account for the value of co-products. These GHG opportunity costs were then added to the direct GHG emissions estimates of each system; the summed values are then plotted against land cost in Fig. 3.

As a sensitivity test of our key assumptions we re-ran these analyses assuming that carbon recovery rates are halved, or that (because of rebound or similar effects[38–40]) half of the area potentially freed from farming is retained under agriculture. These two changes to our assumptions have numerically identical effects, shown in Supplementary Fig. 2. Note that our recovery-based analyses of the GHG costs that farming imposes through land use are conservative, in that they are roughly 30-50% of the values obtained from calculating the GHG emissions from natural habitat clearance (annualised, for consistency with the recovery method, over the following 20 harvests; data not shown).

Code availability. The R codes used for the analyses are available from the corresponding author upon request.

Data availability. The data that support the findings of this study are available from the corresponding author upon request.

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Figure Legends

Fig. 1 | Framework for exploring how different environmental costs compare across alternative production systems. **a,** Hypothetical plot of externality cost *vs* land cost of different, potentially interchangeable production systems (blue circles) in a given farming sector. In this example the data suggest a trade-off between externality and land costs across different systems. **b,** This example reveals a more complex pattern, with additional systems (in green and red circles) that are low or high in both costs.

Fig. 2 | Externality costs of alternative production systems against land cost for five externalities in four agricultural sectors. All costs are expressed per tonne of production (so land cost, for instance, is in ha-years/tonne – i.e. the inverse of yield). Different externalities are indicated by background shading (grey = GHG emissions, blue = water use, pink = N emissions, purple = P emissions, buff = soil loss), and different sectors (Asian paddy rice, European wheat, Latin American beef, European dairy) are shown by icons. Points on plots derived from multi-site experiments (**a, b, c**) and LCAs (**e**) show values for systems adjusted for site and study effects via GLMMs of land cost and externality cost, while arrows show management practices with statistically-significant effects (whose 95% confidence intervals do not overlap zero in the GLMMs; Methods). Pale grey lines in **a**, **b**, **c** and **e** represent 95% confidence intervals of the predictions. In **d** (wheat and N emissions), progressively darker circles depict increasing nitrate application rate (0, 48, 96, 144, 192, 240 and 288 kg N/ha-year). In **f** (beef and GHG emissions, estimated by RUMINANT), different colours show different system types. In **g**-**j** (dairy and four externalities), circles and squares show results for conventional and organic systems, respectively (detailed in Supplementary Table 4). Spearman's rank correlation coefficients (p-values) are **a.** rice-rice: -0.51 (0.002), rice-cereal: -0.36 (0.06), **b.** 0.19 (0.26), **c.** -0.34 (0.14), **d.** -0.21 (0.66), **e.** 0.95 (0.001), **f.** 0.83 (< 0.001), **g.** 0.90 (0.08), **h.** 0.70 (0.23), **i.** 1.00 (0.02) and

j. 1.00 (0.02). Note that these correlation coefficients do not necessarily reflect non-linear relationships (e.g., **d**) accurately.

Fig. 3 | Overall GHG cost against land cost of alternative systems in each sector, including the GHG opportunity costs of land under farming. Y-axis values are the sum of GHG emissions from farming activities (plotted in Figs. 2 a, c, e, g) and the forgone sequestration potential of land maintained under farming and thus unable to revert to natural vegetation (Methods). All costs are expressed per tonne of production. Notation as in Fig. 2. Spearman's rank correlation coefficients (p-values) are **a.** rice-rice: 0.40 (0.017), rice-cereal: 0.80 (< 0.001), **b.** 0.99 (< 0.001), **c.** 0.98 (< 0.001) and **d.** 0.80 (0.13).