The environmental costs and benefits of high-yield farming

How we manage farming and food systems to meet rising human needs will be pivotal to the future of global biodiversity[1,2]. Cutting food waste and excessive consumption of animal products are essential[2–5]. On the supply side, detailed field data from five continents consistently show extinctions would be greatly reduced if future demand could be met by land sparing - boosting yields (production per unit area) on existing farmland while conserving (or restoring) remaining natural habitats[6,7]. But limiting the land cost of agriculture through high-yield farming raises other important concerns because when expressed per unit area, high-yield systems can generate high levels of negative externalities such as greenhouse gas (GHG) and nutrient losses[8,9]. However, such metrics underestimate the overall impacts of lower-yield systems[10]. Here we instead develop a framework quantifying externality costs (including off-site effects) per unit production. Applying this approach to key externalities of the rice, wheat, beef and dairy sectors, we find that associations between externality and land costs across alternative production systems can be positive, rather than being characterised by trade-offs. Per unit production, systems which take up less land often produce lower externalities. For GHG emissions (the best-documented externality) these associations become more strongly positive once the effects of land use are included. We stress that our conclusions are limited by data availability: remarkably few studies quantify externalities alongside yields, and many important externalities are not adequately measured. Moreover some high-yield systems we examined have high externality costs per unit production, and none can generate environmental benefits unless linked with efforts to limit farmland expansion[11,12]. However, our results identify several systems which increase yields while lowering environmental impacts, and more generally suggest that trade-offs among key cost metrics are not as ubiquitous as sometimes perceived.

Detailed empirical research on almost 1800 species from birds to daisies[6,7] reveals so many depend on native vegetation that for most the least bad approach to reconciling biodiversity conservation and food production is high-yield farming coupled with sparing large tracts of intact habitat. Without yield increases in the Cerrado for instance, meeting projected 2050 food demand would require habitat conversion on a scale that would commit ~500 plant species to global extinction[13]. But calculations from here and eight other regions[7,13] around the world consistently show that, provided it can be coupled with setting aside (or restoring) natural habitats[12], high-yield farming has the potential to greatly reduce food production impacts on biodiversity. Lowering the land cost of agriculture appears central to addressing the extinction crisis[1].

A key unresolved issue, however, is that there are many other environmental costs of food production 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[2,4,14]. If these negative externalities were greater for high- than lower-yield farming systems, they would weaken the case for land sparing. Measuring such externalities per unit area of farmland can help identify local-scale impacts[15], but underestimates the overall impact of lower-yield systems that occupy more land for the same level of production[10]. Assessments of externalities also need to include wherever possible the off-site effects of farm interventions (such as cropland for supplementary feeding of livestock, or off-farm grazing for manure inputs to organic systems[10,16]).

We thus suggest that comparisons of the overall impacts of contrasting agricultural systems should focus on the net sum of externality generated per unit of production[7] (paralleling measures of emissions intensity in climate-change analyses). This approach has so far only been adopted for a relatively narrow set of agricultural products[5,17] and farming systems (eg organic *vs* conventional, glasshouse *vs* open-field[10,18]). Here we develop a more general framework, and apply it to a diverse range of 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 the environmental costs of producing a given quantity of a commodity, across alternative production systems. We focus on some better-known externality costs examined in relation to land cost (i.e. 1/yield, as a proxy for impact on native biodiversity), though 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 (Extended Data 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 (Extended Data 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 – which required statistical modelling 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 weak negative associations with land cost across monoculture and rotational systems (assessed separately). For both system types, greater application of organic N lowered land cost but increased emissions (presumably because of feedstock effects on the methanogenic community; Extended Data 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; Extended Data Table 2). Increasing application of inorganic N boosted yield[19], and less irrigation lowered water use while incurring only a modest yield penalty[20]. Sensitivity tests of the rice analyses had little impact on these patterns (Methods; Extended Data Fig. 1).

We found two useable datasets on European wheat, both from the UK (Methods). Data from a three-site experiment varying the N fertilisation regime revealed a complex relationship between GHG and land costs (Fig. 2c), driven by divergent responses[21] 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.

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 statistical analysis to control for potentially confounding study and site effects we found that across multiple LCAs, land-demanding pasture systems generated greater emissions (Fig. 2e), and both land and GHG costs were reduced by pasture improvements (using N fertilization or legumes). This pattern across contrasting pasture systems was confirmed by running RUMINANT[22] (Fig. 2f), a process-based model which also identified 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[23]. Systems with greater use of concentrates (which have less rumen-degradable protein than grass[24]) 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; Extended Data 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[25] 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; Extended Data Fig. 2). These findings thus confirm recent suggestions[26,27] 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.

Our results support three conclusions. First, useful data are worryingly limited. We considered only four sectors and a narrow set of externalities - not including important impacts such as soil health or the effects of pesticide exposure on human health[10]. Even then we found studies reporting yield-linked estimates of externalities scarce, with many important practices undocumented. Yet relatively speaking these are well-studied sectors and externalities. 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 are urgently needed.

However, 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), other interventions appear capable of reducing several costs simultaneously (see also refs [5,18,28,29]). 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.

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 heavy use of pesticides in tropical fruit production, may 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[21]. Perhaps most usefully, profiling existing systems via our framework provides context for evaluating the environmental potential of new technologies and practices.

We close by stressing that for high-yield systems to generate any environmental benefits they must be linked with efforts to reduce rebound effects. Systems which perform well per unit production may be environmentally harmful if higher profits or lower prices stimulate land conversion[11]. Historically, higher yields have led to overproduction of cheap, calorie-rich but nutrient-deficient foods, causing major public health problems[30]. 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[3,30] and directly linked with effective measures to constrain agricultural expansion[12].

References

1. Green, R. E., Cornell, S. J., Scharlemann, J. P. W. & Balmford, A. Farming and the fate of wild nature. *Science* **307,** 550–555 (2005).
2. Godfray, H. C. J. *et al.* Food security: the challenge of feeding 9 billion people. *Science* **327,** 812–818 (2010).
3. Bajželj, B. *et al.* Importance of food-demand management for climate mitigation. *Nat. Clim. Chang.* **4,** 924–929 (2014).
4. Foley, J. A. *et al.* Solutions for a cultivated planet. *Nature* **478,** 337–342 (2011).
5. Ripple, W. J. *et al.* Ruminants, climate change and climate policy. *Nat. Clim. Chang.* **4,** 2–5 (2014).
6. Phalan, B., Onial, M., Balmford, A. & Green, R. E. Reconciling food production and biodiversity conservation: land sharing and land sparing compared. *Science* **333,** 1289–1291 (2011).
7. Balmford, A., Green, R. & Phalan, B. Land for food & land for nature? *Daedalus* **144,** 57–75 (2015).
8. Matson, P. A., Parton, W. J., Power, A. G. & Swift, M. J. Agricultural intensification and ecosystem properties. *Science* **277,** 504–509 (1997).
9. Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R. & Polasky, S. Agricultural sustainability and intensive production practices. *Nature* **418,** 671–677 (2002).
10. Seufert, V. & Ramankutty, N. Many shades of gray – the context-dependent performance of organic agriculture. *Sci. Adv.* **3,** e1602638 (2017).
11. Lambin, E. F. & Meyfroidt, P. Global land use change, economic globalization, and the looming land scarcity. *Proc. Natl. Acad. Sci. U. S. A.* **108,** 3465–3472 (2011).
12. Phalan, B. *et al.* How can higher-yield farming help to spare nature? *Science* **351,** 450–451 (2016).
13. Strassburg, B. B. N. *et al.* Moment of truth for the Cerrado hotspot. *Nat. Ecol. Evol.* **1(4),**

Article No. 0099, DOI: 10.1038/s41559-017-0099 (2017).

14. Pretty, J. Agricultural sustainability: concepts, principles and evidence. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* **363,** 447–465 (2008).

15. Didham, R. K. *et al.* Agricultural intensification exacerbates spillover effects on soil biogeochemistry in adjacent forest remnants. *PLoS One* **10,** e0116474 (2015).

16. Kirchmann, H., Bergström, L., Kätterer, T., Andrén, O. & Andersson, R. Can organic crop production feed the world? In *Organic Crop Production – Ambitions and Limitations* (eds Kirchmann, H. & Bergström, L.) 39–72 (Springer, Dordrecht, The Netherlands, 2008).

17. Nijdam, D., Rood, T. & Westhoek, H. The price of protein: review of land use and carbon footprints from life cycle assessments of animal food products and their substitutes. *Food Policy* **37,** 760–770 (2012).

18. Clark, M. & Tilman, D. Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. *Environ. Res. Lett.* **12,** 64016 (2017).

19. Pittelkow, C. M., Adviento-Borbe, M. A., van Kessel, C., Hill, J. E. & Linquist, B. A. Optimizing rice yields while minimizing yield-scaled global warming potential. *Glob. Chang. Biol.* **20,** 1382–1393 (2014).

20. Carrijo, D. R., Lundy, M. E. & Linquist, B. A. Rice yields and water use under alternate wetting and drying irrigation: a meta-analysis. *F. Crop. Res.* **203,** 173–180 (2017).

21. Smith, K. A. *et al.* The effect of N fertilizer forms on nitrous oxide emissions from UK arable land and grassland. *Nutr. Cycl. Agroecosystems* **93,** 127–149 (2012).

22. Herrero, M. *et al.* Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. *Proc. Natl. Acad. Sci. U. S. A.* **110,** 20888–20893 (2013).

23. Beauchemin, K., McAllister, T. A. & McGinn, S. M. Dietary mitigation of enteric methane from cattle. *CAB Rev. Perspect. Agric. Vet. Sci. Nutr. Nat. Resour.* **4,** 1–18 (2009).

24. Wilkinson, J. M. & Garnsworthy, P. C. Dietary options to reduce the environmental impact of milk production. *J. Agric. Sci.* **155,** 334–347 (2017).

25. IPCC. *2006 IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme* (eds Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T. & Tanabe, K.) (IGES, Hayama, 2006).

26. Gilroy, J. J. *et al.* Optimizing carbon storage and biodiversity protection in tropical agricultural landscapes. *Glob. Chang. Biol.* **20,** 2162–2172 (2014).

27. Lamb, A. *et al.* The potential for land sparing to offset greenhouse gas emissions from agriculture. *Nat. Clim. Chang.* **6,** 488–492 (2016).

28. Cui, Z. *et al.* Pursuing sustainable productivity with millions of smallholder farmers. *Nature* **555,** 363–366 (2018).

29. Notarnicola, B. *et al.* The role of life cycle assessment in supporting sustainable agri-food systems: a review of the challenges. *J. Clean. Prod.* **140,** 399–409 (2017).

30. Tilman, D. & Clark, M. Global diets link environmental sustainability and human health. *Nature* **515,** 518–522 (2014).

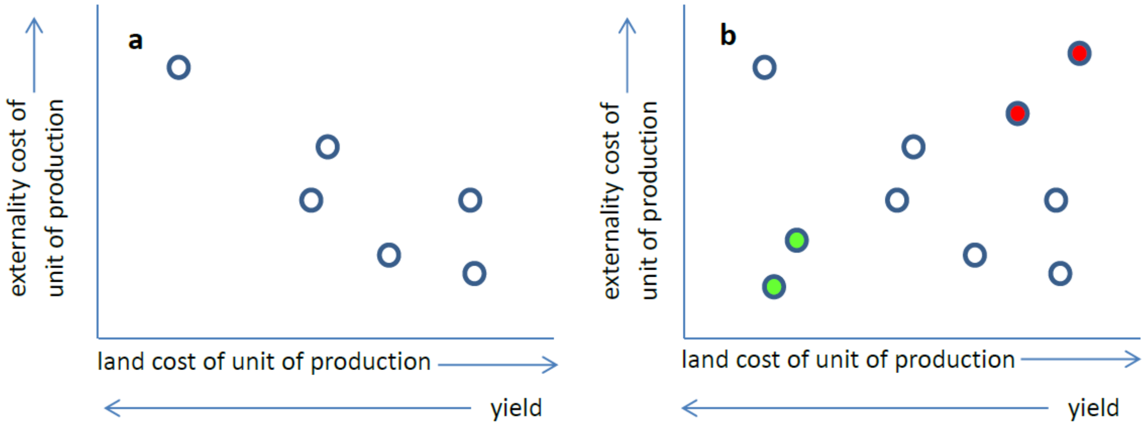

Fig. 1 | Framework for exploring how different environmental costs compare across alternative production systems. **a,** Hypothetical plot of externality cost *vs* land cost of different, potentially interchangeable production systems (blue circles) in a given farming sector. In this example the data 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.

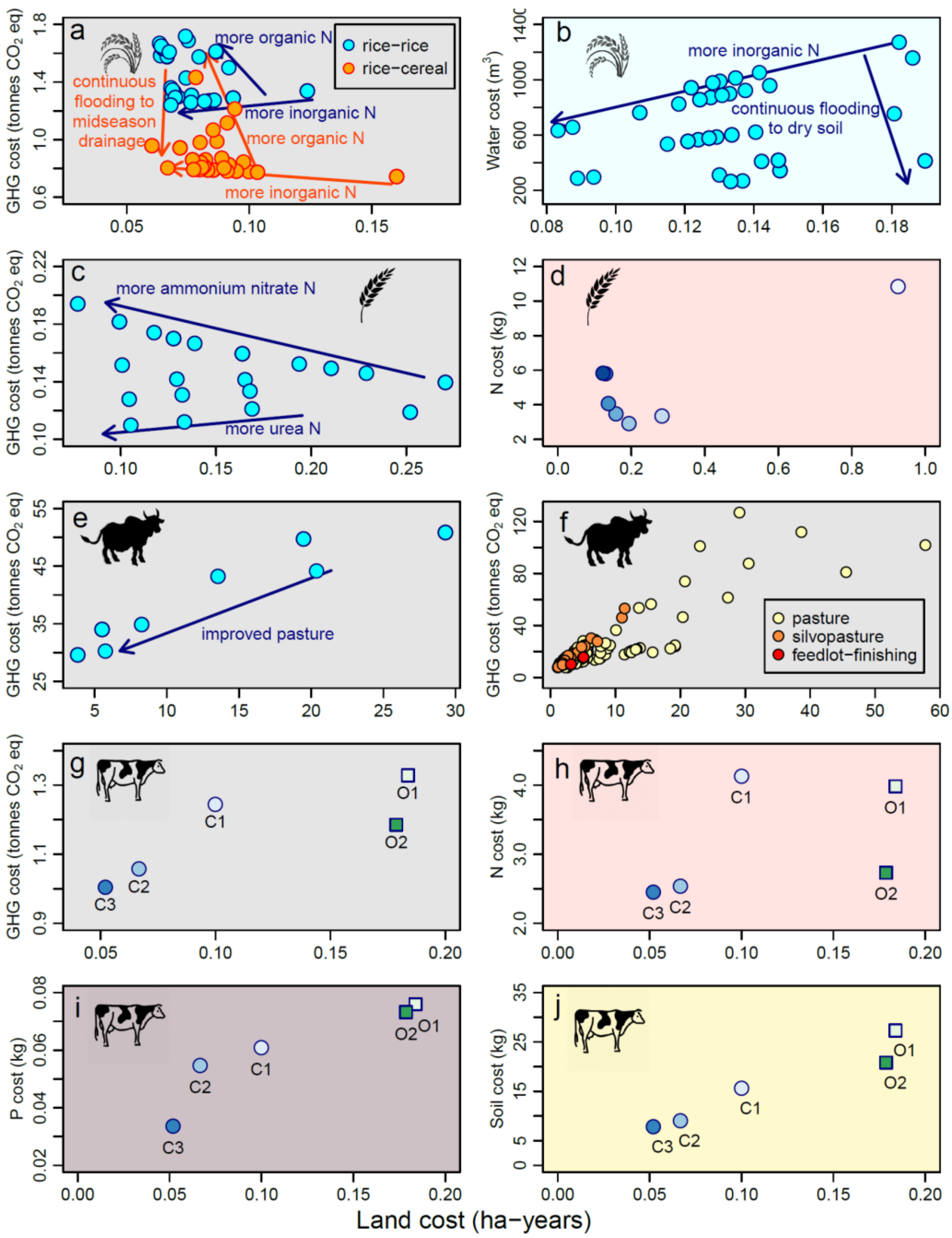

Fig. 2 | Externality costs of alternative production systems against land cost for five externalities in four agricultural sectors. All costs are expressed per tonne of production. Different externalities are indicated by background shading (grey = GHG emissions, blue = water use, pink = N emissions, 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 and LCAs (**a, b, c, e, f**) 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). 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 Extended Data Table 4).

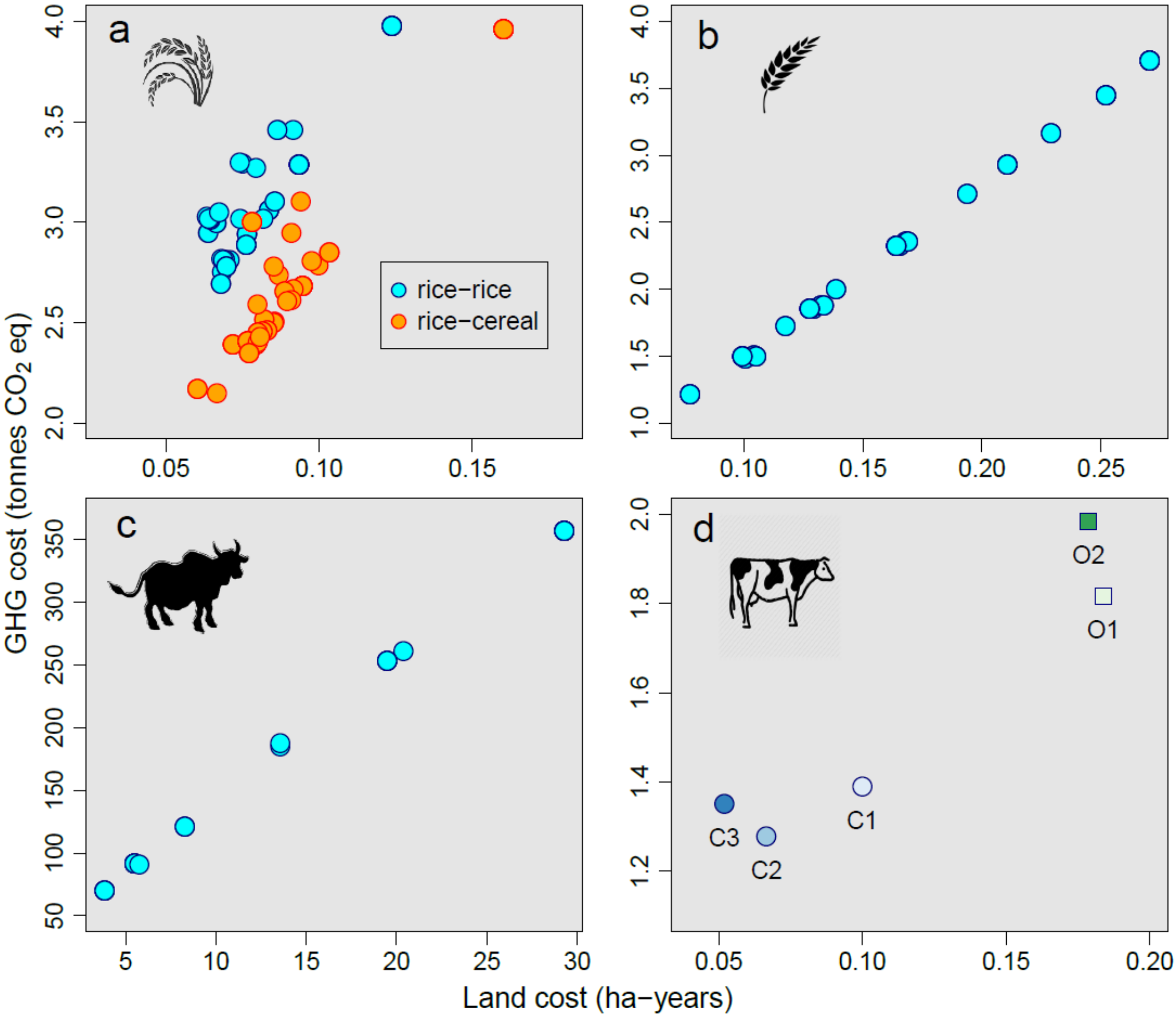

Fig. 3 | Overall GHG cost against land cost of alternative systems in each sector, including the GHG opportunity costs of land under farming. Y-axis values are the sum of GHG emissions from farming activities (plotted in Figs. 2 a, c, e, g) and the forgone sequestration potential of land maintained under farming and thus unable to revert to natural vegetation (Methods). All costs are expressed per tonne of production. Sectors are shown by icons.

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[31]) 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 (Extended Data 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). 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[32] in R version 3.3.1[33] to identify effects of specific management practices on land and externality cost estimates adjusted for potentially confounding biophysical and methodological effects; this adjustment was not needed for data from single-site experiments and process-based models. 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)[34].

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[35–51] 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 [35–37,52]), 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. [31]).

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 [53,54]). 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 (Extended Data 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[55] b(*cf* relative price; Extended Data 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[45,46,52,56–67] 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 predicting 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 (Extended Data 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[56] 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 (Extended Data Fig. 1).

Wheat and GHG emissions. Experimental data for this analysis came from the Agricultural Greenhouse Gas Inventory Research Platform[68–71]. 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 (Extended Data 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[72]. 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[73–80]. 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 (assessed from reported 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%[81]. 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. [74]), 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 (Extended Data 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[22] 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 (Extended Data 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[82], based on system-specific reproductive performance parameters and animal growth rates (which reflected pasture quality and management; Extended Data 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 [31,73]). 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 [25,73]). Carbon sequestration by vegetation could not be included, which is likely to lead to a relative overestimate of GHG emissions from silvopasture[83]. All emissions were converted to CO_2eq units (using conversion factors from refs [25,73] and feedlot manure distribution from ref. [84]) 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, and N, P and soil losses varied with yield (and therefore land cost) across 5 dairy systems representative of UK farm practices (Extended Data 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 [24,85]. Manure management of each system used representative variations of the "manure management continuum"[86] (Extended Data 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[87] 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 [88,89], with yield penalties for organic production from ref. [90]). Because 57% of global beef production originates from the dairy sector[91], 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. [24]), CH_4 and N_2O emissions from manure management (following guidelines in refs [25] and [92]), emissions from N fertiliser applications to pasture (from refs [93,94]), and emissions from feed production (from ref. [95]). 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[96,97], whilst estimates of P and soil losses were based on the Phosphorus and Sediment Yield CHaracterisation In Catchments (PSYCHIC) model[98,99]. 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. [91]) instead of price (see Extended Data 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[100], whose magnitude increases with the area under production (and hence with the land cost of the system). We quantified this GHG cost by combining our land cost estimates of the systems examined in each sector with standard values for the recovery of above-ground and soil biomass[25,101] (Extended Data Table 5). We assumed (in line with IPCC guidelines[25]) that recovery takes 20 years, and (as in ref. [27]) 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[11,102,103]) half of the area potentially freed from farming is retained under agriculture. These two changes to our assumptions have numerically identical effects, shown in Extended Data 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 on reasonable request.

Data availability. The datasets analysed are available from the corresponding author on reasonable request.

References

31. FAO. *FAOSTAT: Food and Agriculture Data* http://www.fao.org/faostat/ (Food and Agriculture Organization of the United Nations, Rome, 2017).
32. Bates, D., Mächler, M., Bolker, B. & Walker, S. Fitting linear mixed-effects models using lme4. *J. Stat. Softw.* **67,** 1–48 (2015).
33. R Core Team. *R: A Language and Environment for Statistical Computing* https://www.r-project.org/ (R Foundation for Statistical Computing, Vienna, Austria, 2016).
34. Guinée, J. B., Heijungs, R. & Huppes, G. Economic allocation: examples and derived decision tree. *Int. J. Life Cycle Assess.* **9,** 23–33 (2004).
35. Shang, Q. *et al.* Net annual global warming potential and greenhouse gas intensity in Chinese double rice-cropping systems: a 3-year field measurement in long-term fertilizer experiments. *Glob. Chang. Biol.* **17,** 2196–2210 (2011).
36. Liu, Y. *et al.* Net global warming potential and greenhouse gas intensity from the double rice system with integrated soil–crop system management: a three-year field study. *Atmos. Environ.* **116,** 92–101 (2015).
37. Chen, Z., Chen, F., Zhang, H. & Liu, S. Effects of nitrogen application rates on net annual global warming potential and greenhouse gas intensity in double-rice cropping systems of the Southern China. *Environ. Sci. Pollut. Res. Int.* **23,** 24781–24795 (2016).
38. Xue, J. F. *et al.* Assessment of carbon sustainability under different tillage systems in a double rice cropping system in Southern China. *Int. J. Life Cycle Assess.* **19,** 1581–1592 (2014).
39. Shen, J. *et al.* Contrasting effects of straw and straw-derived biochar amendments on greenhouse gas emissions within double rice cropping systems. *Agric. Ecosyst. Environ.* **188,** 264–274 (2014).
40. Ma, Y. C. *et al.* Net global warming potential and greenhouse gas intensity of annual rice-wheat rotations with integrated soil-crop system management. *Agric. Ecosyst. Environ.* **164,**

209–219 (2013).

41. Zhang, X., Xu, X., Liu, Y., Wang, J. & Xiong, Z. Global warming potential and greenhouse gas intensity in rice agriculture driven by high yields and nitrogen use efficiency. *Biogeosciences* **13,** 2701–2714 (2016).

42. Yang, B. *et al.* Mitigating net global warming potential and greenhouse gas intensities by substituting chemical nitrogen fertilizers with organic fertilization strategies in rice-wheat annual rotation systems in China: a 3-year field experiment. *Ecol. Eng.* **81,** 289–297 (2015).

43. Zhang, Z. S., Guo, L. J., Liu, T. Q., Li, C. F. & Cao, C. G. Effects of tillage practices and straw returning methods on greenhouse gas emissions and net ecosystem economic budget in rice-wheat cropping systems in central China. *Atmos. Environ.* **122,** 636–644 (2015).

44. Xiong, Z. *et al.* Differences in net global warming potential and greenhouse gas intensity between major rice-based cropping systems in China. *Sci. Rep.* **5,** 17774 (2015).

45. Xu, Y. *et al.* Improved water management to reduce greenhouse gas emissions in no-till rapeseed–rice rotations in Central China. *Agric. Ecosyst. Environ.* **221,** 87–98 (2016).

46. Xu, Y. *et al.* Effects of water-saving irrigation practices and drought resistant rice variety on greenhouse gas emissions from a no-till paddy in the central lowlands of China. *Sci. Total Environ.* **505,** 1043–1052 (2015).

47. Yao, Z. *et al.* Nitrous oxide and methane fluxes from a rice-wheat crop rotation under wheat residue incorporation and no-tillage practices. *Atmos. Environ.* **79,** 641–649 (2013).

48. Xia, L., Wang, S. & Yan, X. Effects of long-term straw incorporation on the net global warming potential and the net economic benefit in a rice-wheat cropping system in China. *Agric. Ecosyst. Environ.* **197,** 118–127 (2014).

49. Zhang, A. *et al.* Change in net global warming potential of a rice-wheat cropping system with biochar soil amendment in a rice paddy from China. *Agric. Ecosyst. Environ.* **173,** 37–45 (2013).

50. Zou, J., Huang, Y., Zong, L., Zheng, X. & Wang, Y. Carbon dioxide, methane, and nitrous oxide emissions from a rice-wheat rotation as affected by crop residue. *Adv. Atmos. Sci.* **21,** 691–698 (2004).

51. Zhou, M. *et al.* Nitrous oxide and methane emissions from a subtropical rice-rapeseed rotation system in China: a 3-year field case study. *Agric. Ecosyst. Environ.* **212,** 297–309 (2015).

52. Yao, Z. *et al.* Improving rice production sustainability by reducing water demand and greenhouse gas emissions with biodegradable films. *Sci. Rep.* **7,** 39855 (2017).

53. Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. *WorldClim – Global Climate Data: WorldClim Version 2* http://www.worldclim.org/version2 (2017).

54. Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. *WorldClim – Global Climate Data: Bioclimatic Variables* http://www.worldclim.org/bioclim (2017).

55. Heuzé, V., Tran, G. & Hassoun, P. *Feedipedia: Rough Rice (Paddy Rice)* https://www.feedipedia.org/node/226 (Feedipedia, a programme by INRA, CIRAD, AFZ and FAO, 2015).

56. Liang, K. *et al.* Grain yield, water productivity and CH4 emission of irrigated rice in response to water management in south China. *Agric. Water Manag.* **163,** 319–331 (2016).

57. Kreye, C. *et al.* Fluxes of methane and nitrous oxide in water-saving rice production in north China. *Nutr. Cycl. Agroecosystems* **77,** 293–304 (2007).

58. Lu, W., Cheng, W., Zhang, Z., Xin, X. & Wang, X. Differences in rice water consumption and yield under four irrigation schedules in central Jilin Province, China. *Paddy Water Environ.* **14,** 473–480 (2016).

59. Jin, X. *et al.* Water consumption and water-saving characteristics of a ground cover rice production system. *J. Hydrol.* **540,** 220–231 (2016).

60. Sun, H. *et al.* CH_4 emission in response to water-saving and drought-resistance rice (WDR)

and common rice varieties under different irrigation managements. *Water, Air, Soil Pollut.* **227,** 47 (2016).

61. Wang, X. *et al.* The positive impacts of irrigation schedules on rice yield and water consumption: synergies in Jilin Province, Northeast China. *Int. J. Agric. Sustain.* **14,** 1–12 (2016).

62. Xiong, Y., Peng, S., Luo, Y., Xu, J. & Yang, S. A paddy eco-ditch and wetland system to reduce non-point source pollution from rice-based production system while maintaining water use efficiency. *Environ. Sci. Pollut. Res.* **22,** 4406–4417 (2015).

63. Shao, G.-C. *et al.* Effects of controlled irrigation and drainage on growth, grain yield and water use in paddy rice. *Eur. J. Agron.* **53,** 1–9 (2014).

64. Liu, L. *et al.* Combination of site-specific nitrogen management and alternate wetting and drying irrigation increases grain yield and nitrogen and water use efficiency in super rice. *F. Crop. Res.* **154,** 226–235 (2013).

65. Chen, Y., Zhang, G., Xu, Y. J. & Huang, Z. Influence of irrigation water discharge frequency on soil salt removal and rice yield in a semi-arid and saline-sodic area. *Water (Switzerland)* **5,** 578–592 (2013).

66. Ye, Y. *et al.* Alternate wetting and drying irrigation and controlled-release nitrogen fertilizer in late-season rice. Effects on dry matter accumulation, yield, water and nitrogen use. *F. Crop. Res.* **144,** 212–224 (2013).

67. Peng, S. *et al.* Integrated irrigation and drainage practices to enhance water productivity and reduce pollution in a rice production system. *Irrig. Drain.* **61,** 285–293 (2012).

68. Bell, M. J. *et al.* Nitrous oxide emissions from fertilised UK arable soils: fluxes, emission factors and mitigation. *Agric. Ecosyst. Environ.* **212,** 134–147 (2015).

69. Bell, M. J. *et al. Agricultural Greenhouse Gas Inventory Research Platform - InveN2Ory: Fertiliser Experimental Site in East Lothian, 2011. Version:1* [dataset]

https://doi.org/10.17865/ghgno606 (Freshwater Biological Association, 2017).

70. Cardenas, L. M., Webster, C. & Donovan, N. *Agricultural Greenhouse Gas Inventory Research Platform - InveN2Ory: Fertiliser Experimental Site in Bedfordshire, 2011. Version:1* [dataset] https://doi.org/10.17865/ghgno613 (Freshwater Biological Association, 2017).

71. Williams, J.R., Balshaw, H., Bhogal, A., Kingston, H., Paine, F. & Thorman, R. E. *Agricultural Greenhouse Gas Inventory Research Inventory Research Platform - InveN2Ory: Fertiliser Experimental Site in Herefordshire, 2011. Version:1* [dataset] https://doi.org/10.17865/ghgno675 (Freshwater Biological Association, 2017).

72. Goulding, K. W. T., Poulton, P. R., Webster, C. P. & Howe, M. T. Nitrate leaching from the Broadbalk Wheat Experiment, Rothamsted, UK, as influenced by fertilizer and manure inputs and the weather. *Soil Use Manag.* **16,** 244–250 (2000).

73. Cardoso, A. S. *et al.* Impact of the intensification of beef production in Brazil on greenhouse gas emissions and land use. *Agric. Syst.* **143,** 86–96 (2016).

74. de Figueiredo, E. B. *et al.* Greenhouse gas balance and carbon footprint of beef cattle in three contrasting pasture-management systems in Brazil. *J. Clean. Prod.* **142,** 420–431 (2017).

75. Dick, M., Abreu Da Silva, M. & Dewes, H. Life cycle assessment of beef cattle production in two typical grassland systems of southern Brazil. *J. Clean. Prod.* **96,** 426–434 (2015).

76. Florindo, T. J., de Medeiros Florindo, G. I. B., Talamini, E., da Costa, J. S. & Ruviaro, C. F. Carbon footprint and Life Cycle Costing of beef cattle in the Brazilian midwest. *J. Clean. Prod.* **147,** 119–129 (2017).

77. Mazzetto, A. M., Feigl, B. J., Schils, R. L. M., Cerri, C. E. P. & Cerri, C. C. Improved pasture and herd management to reduce greenhouse gas emissions from a Brazilian beef production system. *Livest. Sci.* **175,** 101–112 (2015).

78. Pashaei Kamali, F. *et al.* Environmental and economic performance of beef farming systems with different feeding strategies in southern Brazil. *Agric. Syst.* **146,** 70–79 (2016).

79. Ruviaro, C. F., De Léis, C. M., Lampert, V. D. N., Barcellos, J. O. J. & Dewes, H. Carbon footprint in different beef production systems on a southern Brazilian farm: a case study. *J. Clean. Prod.* **96,** 435–443 (2015).

80. Ruviaro, C. F. *et al.* Economic and environmental feasibility of beef production in different feed management systems in the Pampa biome, southern Brazil. *Ecol. Indic.* **60,** 930–939 (2016).

81. Dick, M., Da Silva, M. A. & Dewes, H. Mitigation of environmental impacts of beef cattle production in southern Brazil - evaluation using farm-based life cycle assessment. *J. Clean. Prod.* **87,** 58–67 (2015).

82. Lesnoff, M. *DynMod: a Tool for Demographic Projections of Tropical Livestock Populations Under Microsoft Excel, User's Manual - Version 1* https://cgspace.cgiar.org/bitstream/handle/10568/360/Dynmod_UserManual_v1_MG6.pdf?sequence=1&isAllowed=y (CIRAD, Montpelier, Cedex; ILRI, Nairobi, Kenya, 2008).

83. Broom, D. M., Galindo, F. A. & Murgueitio, E. Sustainable, efficient livestock production with high biodiversity and good welfare for animals. *Proc. R. Soc. B.* **280,** 20132025 (2013).

84. Junior, C. C. *et al.* Brazilian beef cattle feedlot manure management: a country survey. *J. Anim. Sci.* **91,** 1811–1818 (2013).

85. Garnsworthy, P. C. The environmental impact of fertility in dairy cows: a modelling approach to predict methane and ammonia emissions. *Anim. Feed Sci. Technol.* **112,** 211–223 (2004).

86. Chadwick, D. *et al.* Manure management: implications for greenhouse gas emissions. *Anim. Feed Sci. Technol.* **166–167,** 514–531 (2011).

87. DEFRA. *Organic Dairy Cows: Milk Yield and Lactation Characteristics in Thirteen Established Herds and Development of a Herd Simulation Model for Organic Milk Production. Project Report OF0170* http://randd.defra.gov.uk/Default.aspx?Menu=Menu&Module=More&Location=None&Com

pleted=0&ProjectID=8431 (DEFRA, 2000).

88. Wilkinson, J. M. Re-defining efficiency of feed use by livestock. *Animal* **5,** 1014–1022 (2011).

89. Webb, J., Audsley, E., Williams, A., Pearn, K. & Chatterton, J. Can UK livestock production be configured to maintain production while meeting targets to reduce emissions of greenhouse gases and ammonia? *J. Clean. Prod.* **83,** 204–211 (2014).

90. de Ponti, T., Rijk, B. & van Ittersum, M. K. The crop yield gap between organic and conventional agriculture. *Agric. Syst.* **108,** 1–9 (2012).

91. Gerber, P., Vellinga, T., Opio, C., Henderson, B. & Steinfeld, H. *Greenhouse Gas Emissions from the Dairy Sector: A Life Cycle Assessment* http://www.fao.org/docrep/012/k7930e/k7930e00.pdf (Food and Agriculture Organization of the United Nations, Rome, 2010).

92. Brown, K. *et al. UK Greenhouse Gas Inventory, 1990 to 2010: Annual Report for Submission under the Framework Convention on Climate Change* https://uk-air.defra.gov.uk/assets/documents/reports/cat07/1204251149_ukghgi-90-10_main_chapters_issue2_print_v1.pdf (DEFRA, 2012).

93. Misselbrook, T. H., Sutton, M. A. & Scholefield, D. A simple process-based model for estimating ammonia emissions from agricultural land after fertilizer applications. *Soil Use Manag.* **20,** 365–372 (2006).

94. Misselbrook, T. H., Gilhespy, S. L., Cardenas, L. M., Williams, J. & Dragosits, U. *Inventory of Ammonia Emissions from UK Agriculture 2015: DEFRA Contract Report (SCF0102)* https://uk-air.defra.gov.uk/assets/documents/reports/cat07/1702201346_nh3inv2015_Final_1_30092016.pdf (DEFRA, 2016).

95. Vellinga, T. V *et al. Methodology Used in FeedPrint: a Tool Quantifying Greenhouse Gas Emissions of Feed Production and Utilization, Report 674* (Wageningen UR Livestock Research, Lelystad, The Netherlands, 2013).

96. Anthony, S.G., Quinn, P., Lord, E. Catchment scale modelling of nitrate leaching. *Asp. Appl. Biol.* **46,** 23–32 (1996).

97. Wang, L. *et al.* The changing trend in nitrate concentrations in major aquifers due to historical nitrate loading from agricultural land across England and Wales from 1925 to 2150. *Sci. Total Environ.* **542,** 694–705 (2016).

98. Davison, P. S., Lord, E. I., Betson, M. J. & Strömqvist, J. PSYCHIC – A process-based model of phosphorus and sediment mobilisation and delivery within agricultural catchments. Part 1: Model description and parameterisation. *J. Hydrol.* **350,** 290–302 (2008).

99. Collins, A. L. & Zhang, Y. Exceedance of modern 'background' fine-grained sediment delivery to rivers due to current agricultural land use and uptake of water pollution mitigation options across England and Wales. *Environ. Sci. Policy* **61,** 61–73 (2016).

100. Koponen, K. & Soimakallio, S. Foregone carbon sequestration due to land occupation - the case of agro-bioenergy in Finland. *Int. J. Life Cycle Assess.* **20,** 1544–1556 (2015).

101. Guo, L. B. & Gifford, R. M. Soil carbon stocks and land use change: a meta analysis. *Glob. Chang. Biol.* **8,** 345–360 (2002).

102. Ewers, R. M., Scharlemann, J. P. W., Balmford, A. & Green, R. E. Do increases in agricultural yield spare land for nature? *Glob. Chang. Biol.* **15,** 1716–1726 (2009).

103. Byerlee, D., Stevenson, J. & Villoria, N. Does intensification slow crop land expansion or encourage deforestation? *Glob. Food Sec.* **3,** 92–98 (2014).

Acknowledgements We are grateful for funding from the Cambridge Conservation Initiative Collaborative Fund and Arcadia, the Grantham Foundation for the Protection of the Environment, the Kenneth Miller Trust the UK-China Virtual Joint Centre for Agricultural Nitrogen (CINAg, BB/N013468/1, financed by the Newton Fund via BBSRC and NERC), BBSRC (BBS/E/C/000I0330), DEVIL (NE/M021327/1), U-GRASS (NE/M016900/1), Soils-R-GRREAT (NE/P019455/1), N-Circle (BB/N013484/1), BBSRC Soil to Nutrition (S2N) strategic programme (BBS/E/C/000I0330), UNAM-PAPIIT (IV200715), the Belmont Forum/FACEE-JPI (NE/M021327/1 'DEVIL'), and the Cambridge Earth System Science NERC DTP (NE/L002507/1). We thank Frank Brendrup, Emma Caton, Achim Dobermann, Thiago Jose Florindo, Ellen Fonte, Ottoline Leyser, Andre Mazzetto, Jemima Murthwaite, Farahnaz Pashaei Kamali, Rafael Olea-Perez, Stephen Ramsden, Claudio Ruviaro, Jonathan Storkey, Bernardo Strassburg, Taro Takahashi, Mark Topliff, Joao Nunes Vieira da Silva, David Williams, Xiaoyuan Yan and Yusheng Zhang for advice, data or analysis.

Author Contributions AB, TA, HB, DC, DE, RF, PG, RG, PS, HW, AW and RE designed the study and performed the research, DB, JC, TF, EG, AG-H, JHM, MH, FH, AL, TM, BP, BS, JV and EzE contributed and analysed data and results, and all authors contributed substantially to the analysis and interpretation of results and writing of the manuscript.

Author Information The authors declare no competing financial interests. Correspondence and requests for materials should be addressed to AB (apb12@cam.ac.uk).

Extended Data titles and legends

Extended Data Table 1 | Types of data used for investigating each sector-externality combination, and (*in italics*) combinations which were not considered important or which we were unable to assess.

*LCA = Life Cycle Assessment

Extended Data Table 2 | Details of Generalised Linear Mixed Models for the effect of management variables and covariates on land and externality costs. Estimated coefficients are shown; those whose 95% confidence intervals (in parentheses) did not overlap zero are in bold. Tillage in Rice-GHG models represents the effect of a tillage regime (compared to a no-tillage regime). Irrigation in Rice-GHG models is for the effect of episodic midseason drainage compared to continuous flooding. The effect of irrigation in Rice-Water models is based on five levels compared to continuous flooding: continuous flooding with a drainage (CF-drain), alternative wetting and drying (AWD), controlled irrigation (CI), mulches or plastic films (F-M) and long periods of dry soil (Dry). In Beef-GHG models, improved breed represents the effect of using an improved breed relative to an unimproved breed.

Extended Data Table 3 | Summary of input settings used to characterise contrasting Brazilian beef production systems in RUMINANT and DYNMOD.

Extended Data Table 4 | Profile of the key features of our contrasting model systems of UK dairy production.

*an animal is an adult cow plus her replacements

Extended Data Table 5 | Sources of values used to estimate the rate of accumulation of above- and below-ground carbon when farmland recovers to natural habitat.

Extended Data Fig. 1 | Sensitivity tests of associations between externality costs and land costs. Plots are modified versions of those in Fig. 2. **a,** The effect in rotational paddy systems of allocating land and GHG costs between rice and co-products based on their relative contribution to production of energy (Methods). **b,** The effect on the association between water cost and land cost of paddy rice of excluding early-season data from the only study reporting data for two seasons per year. **c-f**, The effects in European dairy systems of allocating land and externality costs between milk and its beef co-product in proportion to their relative contribution to production of protein per unit area of farmland (Methods). All notation as in Fig. 2.

Extended Data Fig. 2 | Sensitivity tests of associations between overall GHG costs (including GHG opportunity costs of land use) and land costs. Plots are modified versions of those in Fig. 3, but show the effects of assuming either that carbon sequestration rates of recovering habitat are half those given in IPCC guidelines or that half of the area potentially freed from farming because of higher yield is retained under agriculture (Methods); these assumptions have identical effects. Notation as in Fig. 3.