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Mapping the ratio of agricultural inputs to yields reveals areas with potentially less sustainable farming

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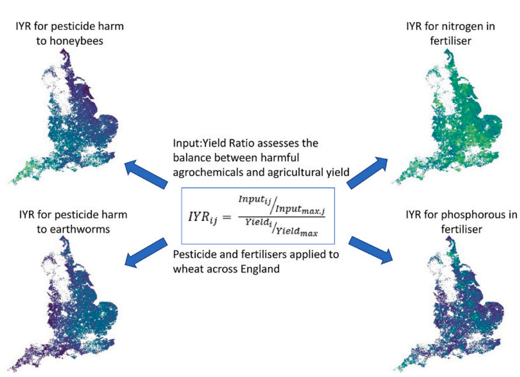
HIGHLIGHTS

- Balancing benefits against harm from agrochemicals will aid sustainable farming.
- We propose the Input:Yield Ratio IYR to assess this balance for multiple inputs.
- We use novel data to map IYR values for different inputs across England.
- We find hotspots where the IYR is high for all input types.
- The IYR could be used broadly to highlight where farming may be less sustainable.

GRAPHICAL ABSTRACT



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ABSTRACT

Fertilisers and pesticides are major sources of the environmental harm that results from farming, yet it remains difficult to target reductions in their impacts without compromising food production. We suggest that calculating the ratio of agrochemical inputs to yield can provide an indication of the potential sustainability of farmland, with those areas that have high input relative to yield being considered as less sustainable. Here we design an approach to characterise such Input to Yield Ratios (IYR) for four inputs that can be plausibly linked to environmental impacts: the cumulative risk resulting from pesticide exposure for honeybees and for earthworms, and the amount of nitrogen or phosphorus fertiliser applied per unit area. We capitalise on novel national-scale data to assess IYR for wheat farming across all of England. High-resolution spatial patterns of IYR differed among the four inputs, but hotspots, where all four IYRs were high, were in key agricultural regions not usually characterised as having low suitability for cropping. By scaling the magnitude of each input against crop yield, the IYR does not penalise areas of high yield with higher inputs (important for food production), or areas with low yields but which are achieved with low inputs (important as low impact areas). Instead, the IYR provides a globally

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applicable framework for evaluating the broad patterns of trade-offs between production and environmental risk, as an indicator of the potential for harm, over large scales. Its use can thus inform targeting to improve agricultural sustainability, or where one might switch to other land uses such as ecosystem restoration.

1. Introduction

Intensive agriculture continues to be a major cause of environmental harm. Farming is an essential activity, but it has multiple negative impacts including conversion and degradation of ecosystems, net greenhouse gas emissions, and the application of agrochemicals (Foley et al., 2005; Ramankutty et al., 2018). Agrochemicals applied to managed crops include a range of pesticides (i.e., chemicals that target any plant, animal, fungal or microbial pest), which can be toxic not just to their intended target species but also to a range of related or unrelated non-target species (Tang et al., 2021; Tudi et al., 2021; Woodcock et al., 2017). Fertiliser addition to farmland also causes environmental problems, such as the widespread eutrophication of water ecosystems (Carpenter, 2008; Sebilo et al., 2013). These forms of agrochemical pollution contribute to making intensive agriculture one of the major global drivers of biodiversity loss, and declines in many ecosystem services (IPBES, 2019; Isbell et al., 2022).

Solving the problems from agricultural impacts is not straightforward, due to the need to provide people globally with plentiful and nutritious food. Approaches to reducing and reversing harm from intensive farming range from targeted amelioration of its more damaging aspects, such as by using precision agriculture (Finger et al., 2019), through a more complete overhaul of the farming system such as by implementing organic or regenerative agriculture (Schulte et al., 2022), to taking land out of farming altogether such as by ecosystem restoration or rewilding (Newton et al., 2021). The problem is that many of these activities impact negatively on the yield or total production of foodstuffs, with the more radical alternatives having greater impacts, for example by taking land out of production (Eva-Marie Meemken and Matin Qaim, 2018). Indeed, better understanding the trade-offs between food production and environmental protection is one of the major research issues of our time (Balmford et al., 2018; Foley et al., 2011).

Any plan to manage trade-offs between agricultural yield and environmental harm needs to consider where best to target activities spatially, to provide the greatest environmental benefits while minimising impacts on yields (Folberth et al., 2020). Current spatial targeting approaches focus on finding locations most suitable for conservation activities (e.g. planting trees) (Bastin et al., 2019), where it least suitable to do agriculture (e.g. because yields are relatively low) (Naidoo and Iwamura, 2007), or areas where there is synergy between these two options (Redhead et al., 2022). An alternative approach, which allows more nuance in ameliorative actions, is to consider how agrochemical inputs and agricultural production vary in relation to each other, with the idea of balancing the environmental risk of agrochemicals (and their links to environmental harm) against the benefits of enhancing agricultural yield. Here we explore this idea by analysing the spatial variation in the use of agrochemicals in relation to the amount of agricultural production.

One plausible way to assess variation in potential agrochemical harm could be simply to determine where the highest amounts of agrochemicals are used. However, yield and inputs are not necessarily tightly linked; for example, harvested food contains only a small proportion of the nitrogen applied in fertilisers (Chatzimpiros and Harchaoui, 2023). As a result, the yield per unit of any specific agrochemical input often varies spatially (Godwin et al., 2003). Indeed, it is well known that both the yield of any particular crop and the application of agrochemical inputs, i.e. fertilisers and pesticides, to that crop vary strongly over landscapes and regions, and that this variation is related to environmental drivers including climate, soil characteristics, and pest identity and load (Malaj et al., 2020; Redhead et al., 2020; Swaney et al., 2018). Furthermore, as well as environmental drivers, agrochemical use is also related to social factors including farming culture, agronomic advice and the attitude and knowledge of individual farmers (Pedersen et al., 2019; Sharma et al., 2011). As a result, focussing only on inputs would not take account of the fact that some areas with high inputs may be high yielding, so any focus on changing management in these areas may have a large impact on food production. Conversely, targeting low yielding areas may be less impactful for reducing harm if these also have low inputs. We therefore suggest that one might ideally target areas that have high input:yield ratios, i.e. where high amounts of inputs are used in relation to each unit of crop yield, if seeking to reduce the broad-scale impacts of farming on ecosystems.

This Input:Yield Ratio, IYR, has connotations of metrics describing agricultural use/input intensity (Temme and Verburg, 2011), but these tend to consider inputs per unit area rather than per unit yield. When applied to fertilisers, the IYR is a reformulation of equations used to describe Nitrogen N or Phosphorus P 'Use Efficiency' (NUE, PUE), which have different definitions, but can be calculated as the crop yield divided by the amount of fertiliser used (Lassaletta et al., 2014). As such, the inverse of the IYR is the UE ratio for fertilisers, although there is no analogous metric for pesticide use. Use Efficiency is often regarded as an approach for predicting the yield increase of a crop for a certain increase in fertiliser within a given context (Zhang et al., 2015). However, these metrics can also be used to indicate the environmental sustainability of a cropping system (Lassaletta et al., 2014), as is our aim here. Indeed, we argue that strong spatial variation in IYR would suggest that inputs do not precisely predict yield in general, especially as inputs may not be finely tuned to local biophysical conditions, but subject to a range of socio-ecological factors (Nkurunziza et al., 2020). For this reason, the IYR in our formulation represents potential harm in terms of the amount of agrochemical input in relation to the yield (i.e. Input/Yield rather than vice versa).

The IYR concept as outlined requires nuance. First, the amounts of the individual agrochemical inputs (different types of pesticide or fertiliser components) will not vary spatially in the same way, as the pressures they are intended to address (i.e., populations of different pests, and availability of different soil nutrients) are not necessarily related. Second, the potential for risk, as an indicator of the potential to cause harm, due to agrochemical input is not a simple product of the amount applied. Fertilisers supply several nutrients, in particular nitrogen and phosphorus compounds, which have different impacts on the wider environment and so different input:impact ratios (Guignard et al., 2017). Pesticides are even more complex, with individual crops receiving a mixture of chemicals through the season to combat a wide range of pest types. Each pesticide type affects different species to different extents in a manner related to each species' vulnerability to each active ingredient (Mancini et al., 2020; Spurgeon et al., 2020).

Spatio-temporal patterns in NUE and PUE have been studied previously (Heuer et al., 2017; Lassaletta et al., 2014), although not generally with the aim of highlighting areas with less sustainable cropping. Concerning pesticides, the IYR or related concepts have not yet been pursued probably due largely to lack of information on large (e.g., national) scale patterns in agrochemical use and crop yield (Mancini et al., 2020). In this paper we make use of detailed spatial data on yield and agrochemical use to undertake the first evaluation of the balance between yield and agrochemical inputs for a major arable crop at national scale. We focus on wheat because it is by far the dominant crop by land area in England, as it is in many countries around the world. For example, ca 1.65 Mha were grown in England in 2022, out of 3.74 Mha of all arable crops (Defra, 2022). In all areas where wheat is grown, we assess inorganic fertiliser inputs in terms of N and P, which are major sources of agricultural damage to the environment globally (Guignard et al., 2017), and also the scaled cumulative input:sensitivity ratio for two non-target species, honeybees and earthworms, for all applied pesticide active ingredients. We combined this information with available yield data to derive maps of IYR for N, P, and honeybee and earthworm risk, to provide a framework for identifying those locations where wheat farming may be least sustainable and, thus, where one might consider targeting ameliorative actions that also take account of impacts on crop production.

2. Methods

We assessed spatial variation in winter wheat yields and the agrochemicals applied to this crop across England, using spatially-explicit, national-extent estimates of variables, which we combined to calculate IYR values. All datasets (Table 1) were drawn from the period 2010–2017, although the different periodicity of agricultural surveys for yield, fertiliser and pesticide data, and the availability of Sentinel data for crop mapping, means that the datasets cover slightly different ranges within this period. To address this issue we calculated averages across the available years for each dataset.

All maps (individual variables and IYR values) were produced at 1 km resolution using interpolation approaches which are detailed in the following sections. We chose a resolution of 1 km to reflect spatial patterns across England and because this is intermediate between the scale of the typical English field and farm: that is, we avoid attempting to model per field estimates, which have a high level of uncertainty, while capturing the behaviour of a typical farm system in a given area. Due to the interpolation procedures used, the maps should be seen as describing regional patterns rather than identifying specific localities with high or low IYR. Nor should they be seen as representing the actual yields or agrochemical regimes of individual farms within each 1 km cell.

2.1. Yield mapping

Wheat yield data (t/ha) are collected as part of the annual June Survey of Agricultural and Horticultural activity undertaken by the UK Department for Environment, Food & Rural Affairs (Defra) (Defra, 2018). Data are collected annually through a randomly sampled survey of farm holdings, stratified by their theoretical labour requirement - a proxy of holding size. We used winter wheat yield data for the 2010–2016 harvests, amounting to 15,490 distinct data points. We removed yield values of 0 t/ha (likely resulting from individual crop failures, and not usefully indicative of spatial patterns in yield) and crops used for silage (as a different part of the wheat plant is harvested, yields cannot be meaningfully compared with grain crops).

We created annual wheat yield maps by interpolating the individual yield data points to a 1 km grid using the gstat R package (Gräler et al., 2016) and calculating single values for each grid cell. To do this we implemented an inverse distance weighted (IDW) decay model which provided smoothed estimates across space and ensured the prediction was not influenced solely by neighbours but considered the wider landscape. The locations of all data were used to construct the IDW surface (i.e., all data points influence the calculated value at any given location) with the power parameter determining distance decay set to 2. Cell values were then averaged across years to provide a 1 km average yield map for 2010–2016 (Fig. A.1). We identified and excluded grid cells in which winter wheat is not grown using the UKCEH Land Cover plus: Crop map 2017 (UKCEH, 2017) and applied this as a mask to our average yield map.

Table 1
The datasets used to calculate the Input:Yield Ratio, IYR over England.

Variable	Resolution	Time period	Source
Wheat yield (t/ha)	Individual holdings, annual	2010–2016	June Survey of Agricultural and Horticultural activity (Defra, 2018)
Fertiliser applications (kg/ha)	Individual holdings, annual	2010–2015	British Survey of Fertiliser Practice (Defra, 2022)
Pesticide applications (kg/ha)	County, biennial	2012–2016	Pesticide Usage Survey (Fera, 2022)

2.2. Fertiliser mapping

Application rates (kg/ha) of nitrogen (N), and phosphorus (P) to winter wheat are collected during the annual British Survey of Fertiliser Practice (DEFRA, 2022). A different sample of farms is selected for the survey each year, spanning the range of farm sizes and holding types. This random sample of holdings is bolstered by an additional core group of respondents which comprise <20 % of the overall sample size. We used data relating to fertiliser applications to winter wheat crops for 2010–2015, giving us an average of 3618 records per year. Following similar methodology to that used for the Land Cover plus Fertilisers (Osório et al., 2019) product, application rates for N and P were interpolated for each year, again using IDW across a 1 km grid. We averaged annual interpolations across years and masked as previously described to exclude grid cells which did not grow winter wheat (Figs. A.2, A.3).

2.3. Pesticide mapping

We produced maps of the application rates of 121 pesticide active ingredients on winter wheat crop areas at 1 km resolution, following the methodology used to create CEH Land Cover® Plus: Pesticides (Jarvis et al., 2020). The Pesticide Usage Survey (FERA, 2022) (PUS) provides data on annual total applications of each active ingredient (in kg) per crop, as well as the area of each crop, at the level of the 48 English counties. We calculated county-level active ingredient application rates (kg/ha/yr) for winter wheat, averaged over the years 2012–2016. We spatially smoothed estimates using a kriging approach applied in INLA-SPDE using the R-INLA package. We did this to avoid hard boundaries between counties and to smooth over counties which had no records in a certain year due to the design of the PUS. As above, we excluded areas which had not grown any winter wheat. Kriging was considered a more appropriate method for interpolating pesticide applications due to the smaller size and coarser resolution of the input data.

The risk resulting from the use of a pesticide active ingredient is a product of the nature of the environment the chemical enters, which can affect fate and exposure, and the inherent sensitivity and ecology of the considered species. The capacity to fully predict species-specific risk remains the subject of considerable uncertainty. This includes in understanding how different soil types and climate conditions act to affect exposure and also the sensitivities of the vast majority of potentially exposed species, which remain untested. Given this uncertainty, to assess potential pesticide effects within the IYR framework, a pragmatic approach that makes use of the data that is available was needed. The approach taken to assess and ultimately map pesticide risk potential recognises that different active ingredients will have different input: sensitivty ratios for different species (Spurgeon et al., 2020). As a result, simply summing the weights of all active ingredients applied within a km^2 would be uninformative. Instead, we scaled pesticide inputs by their quantified toxicity for two different receptor species. The two species selected were the honeybee *Apis mellifera* and earthworm *Eisenia fetida*. Previous meta-analyses and comparative studies have highlighted that toxicity measured for *A. mellifera* and *E. fetida* may not be representative for other bee and earthworm species (Pelosi et al., 2013; Robinson et al., 2021; Tosi et al., 2022). Further, the ecology of these species means that they may not always be exposed or, in the case of *E. fetida*, even present within, UK cereal cropping systems. However, their selection reflects the fact that these two species are among those most commonly assessed during regulatory pesticide testing. Hence, their use provides a far greater range of information on sensitivity for many different active ingredients (Yatoo et al., 2022). Using this data we are, therefore, able to provide a more complete assessment of the cumulative potential risk of the range of different applied pesticide for *A. mellifera* and *E. fetida* than would be possible for almost any other species, although of course the results apply only to these species. For the wider development of the IYR, the use of these two species for cumulative risk calculation is not prescriptive. If suitable toxicity information can be generated for alternative taxa or species, then it would be possible to conduct a similar analysis for those species using the same overall framework.

For each active ingredient identified from the PUS winter wheat data, we calculated the indicative potential risk to honeybees and to earthworms for each 1 km in which wheat was grown. Firstly, to assess species sensitivity, we identified a representative hazard value; the 'Predicted No Effect Concentration' (PNEC). To calculate the PNEC, we obtained the lowest 96 h lethal concentration for 50 % of individuals (LC_{50}) values for bees (μg/bee) from oral or contact exposure and the chronic 28 day No Observed Effect Concentration (NOEC) values (mg/kg soil) for earthworms from toxicity tests. The data for these endpoints were obtained mainly from the Pesticide Properties Database (Lewis et al., 2016), which includes all data reported in the regulatory dossier for each active ingredient. In cases with a missing or "unbounded" (i.e., the toxicity value was only stated as $>$ or $<$ a specific value) value, we searched the published literature for definitive values, which we favoured. If no alternative was available, we used the unbounded value. To derive the PNEC for effects from these toxicity metrics, we divided the bee 96 h LC_{50} by two factors both of 10, one accounting for the conversion of effects on mortality to effects on sub-lethal traits and the second to account for the difference in effect severity between short (96 h) and long-term (life-time) exposure (Hesketh et al., 2016). For the earthworm PNEC calculation, we divided the reproduction NOEC value by a factor of 10 to account for the difference between short-term laboratory exposure and long-term field effects. The PNEC values used are listed in Table A.1.

We converted pesticide usage amount (application rates) to estimated exposure of earthworms and honeybees in the same units for which the toxicity data were available, considering both the species and the exposure route (spray, seed treatments or soil application). For earthworms, exposures for all active ingredients were calculated in terms of unit area and the pesticide was assumed to be evenly distributed through the top 5 cm of the soil with a bulk density of 1.5 g/cm^3. For honeybees, oral exposure via spray treatment was calculated using the US-EPA Tier 1 exposure estimation tool Bee-Rex v1.0 (US-EPA, 2014), which provides separate exposure estimations per bee, based on the pesticide application route, in μg/bee/day. Foliar spray concentration in nectar and pollen is calculated from the application rate (in kg/ha)*98 and individual exposure per day in μg/bee/day is calculated from assumed daily nectar (292 mg/day) and pollen (0.041 mg/day) intake. Seed treatments have a constant oral exposure of 0.292 μg/bee/day and soil applications were assumed to have zero oral exposure. Contact exposure for bees was assumed to be constant across application routes with a multiplier of 2.4 times application rate.

Finally, we calculated hazard quotients for the individual active ingredients as total exposure divided by toxicity (PNEC) value for that species for each active ingredient. Hazard quotients were then summed across all actives to give the mixture risk. These mixture hazard quotient values were used as the metric of potential risk to honeybees and to earthworms (Figs. A.4, A.5) (NB, the mixture risk quotient units are not comparable between endpoints and should be considered on a relative scale only, therefore, all maps presented are shown scaled by the maximum value as required by the IYR calculation).

2.4. Input:Yield Ratio (IYR) calculations

We conceptualise the IYR as a continuous, relative measure of the balance of agrochemical inputs (i.e., amount of each fertiliser component, and potential risk from the combined applied pesticides to particular species groups) to the yield obtained. The IYR is calculated using scaled rather than absolute values, with the maximum value in each yield and input dataset set as 1, so that input and yields are expressed proportionally to each other. Eq. (1) shows the IYR for a grid cell *i* and input type *j* calculated as the ratio of proportional input to proportional yield. Subscript *max* is the maximum value across all spatial 1 km grid cells.

$$IYR_{ij} = \frac{Input_{ij}/Input_{max,j}}{Yield_i/Yield_{max}} \tag{1}$$

We calculated four IYR values for each grid cell using the four scaled agrochemical input datasets: N and P fertiliser, and honeybee and earthworm pesticide risk. The IYR can take any positive value, and areas with relatively high input but relatively low yields will have the highest IYR values. Because the IYR is calculated relative to the maximum of each input variable its value will be sensitive to high outliers in either input or yield measures. We assessed the ranges of the five variables and found all to be within reasonable limits with no obvious outliers (Figs. A.1-A.5). But a IYR $\approx$ 1 should not be seen as a perfect balance of yield to inputs, as the IYR values are relative, not absolute.

Because the four agrochemical inputs considered are not directly comparable it is not appropriate to calculate an overall input metric. Instead, we identified areas with consistently high IYR across the different types of input by intersecting the four IYR maps and extracting cells in which every individual IYR map had a score in the upper 25th percentile. As the selected percentile is arbitrary, we repeated this procedure using the upper 50th percentiles.

Finally, we asked whether the IYR values simply reflect the quality of the land for agriculture. We examined this through the widely-used Agricultural Land Classification (ALC) system for England (MAFF, 1988). ALC uses climate, soil and topographic characteristics to grade land into five classes of quality for agriculture, as well non-agricultural and urban (MAFF, 1988). The combinations of these characteristics are considered to affect the range of crops that can be grown, the yield of crops, the consistency of yield, and the cost of producing the crop. The highest graded land (ALC 1) is considered the most productive for wide range of agricultural and horticultural crops and efficient in response to inputs. Grades 1 and 2 form about 21 % of farmland in England. With the logic that poorer land requires more agricultural inputs, we hypothesised that high IYR cells would be in poorer quality ALC classes, while low IYR cells would have high ALC grades. Using ALC at 1 km resolution, we determined how ALC grades mapped onto the cells which were in the highest 25th percentiles of all for IYR types ('high IYR'). We repeated this for the cells which were in the lowest 25th percentiles of all for IYR types ('low IYR').

3. Results

3.1. Areas of highest IYR vary among different input types

The four IYR types show different frequency distributions and spatial patterns across England (Fig. 1). All show strong variation, with the higher IYR values being more than double (potential hazard to earthworms) to >100-times (phosphorus) the lower values. IYRs for fertiliser inputs have broadly normal frequency distributions, although with long tails. These tails show potential areas of high mismatch between yields and inputs, where yields are either much higher (very low IYR) or much lower (very high IYR) than average for a given level of fertiliser application. We repeat that because the exact IYR value is determined by the ranges of values for both yield and the input, IYR = 1 has no particular

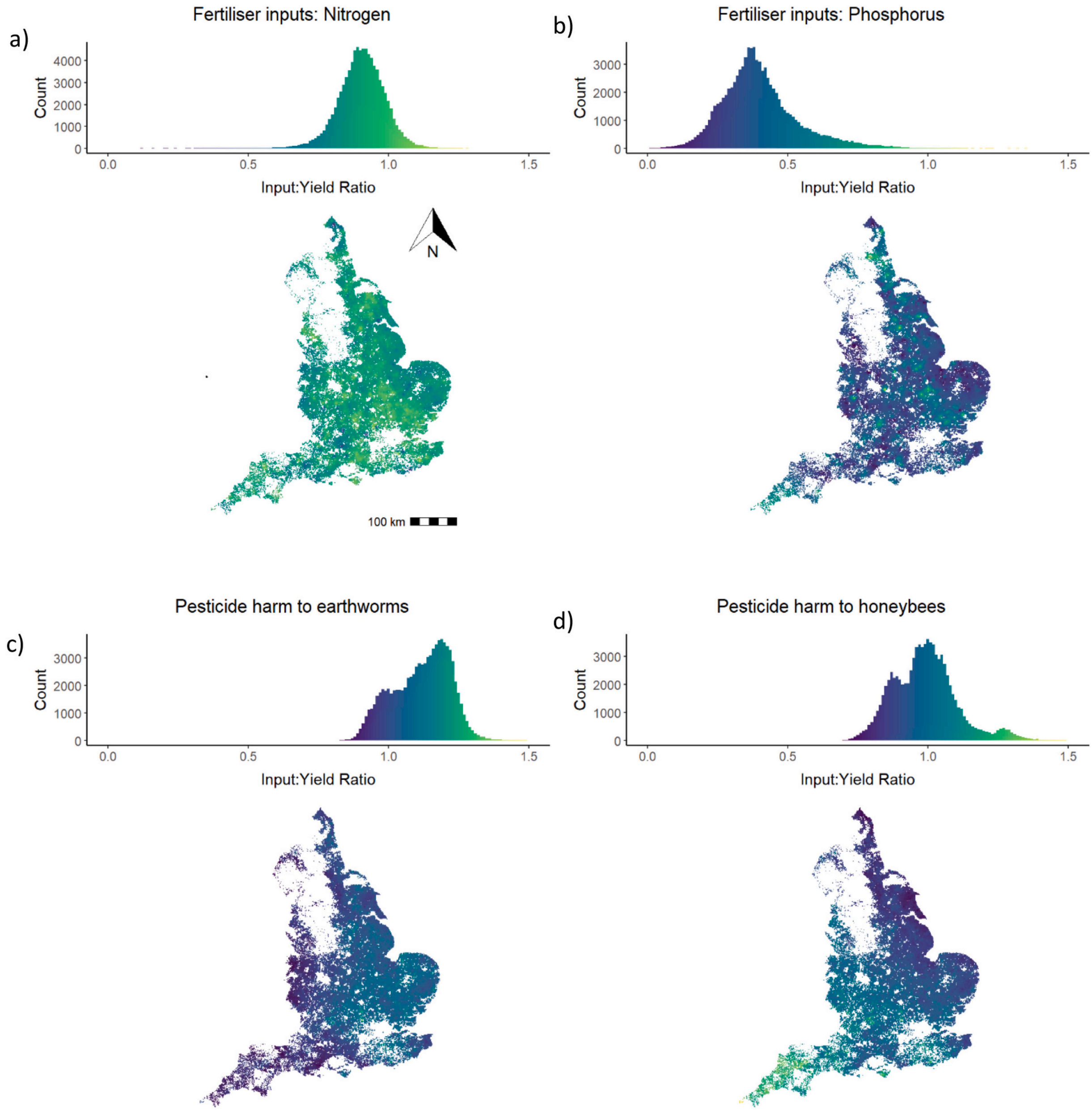

Fig. 1. Frequency distributions and maps, at 1 km resolution, of the Input:Yield Ratios over England for two fertiliser-related and two pesticide-related input types in relation to winter wheat yield. Fertiliser values are based simply on the amount used, while pesticide values are scaled by the toxicity of the set of active ingredients to the specific receptor group. A higher value indicates greater relative inputs for the wheat yield obtained. Colours in the maps match those in the histograms. No wheat was grown in the white areas.

meaning. One should focus rather on any IYR value relative to the distribution of IYR values. Mapping these fertiliser IYRs shows high sub-regional variation rather than broad-scale national patterns. For wheat, N is typically applied separately to P, and this is reflected in the fact that their IYR maps differ and the values per cell are only moderately correlated (Pearson correlation = 0.3).

Distributions of values for pesticide IYRs show bi- or tri-modal distributions, potentially driven by different active ingredients contributing to the overall pesticide risk. Interestingly, the spatial distributions for the two pesticide IYRs are largely contrasting. The earthworm map indicates highest IYR values (i.e., greater potential risk from pesticide inputs for the wheat yield obtained) in the east of England whereas for honeybees the highest IYR values are in the west. Closer inspection shows that potential risk values for worms and honeybees are driven by different sets of active ingredients (Fig. 2), with associated differences in spatial distributions (Figs. A.6, A.7). For both, a single active ingredient dominates although several active ingredients make significant contributions. For earthworms, the dominant chemical is epoxiconazole, a broad-spectrum fungicide. For honeybees, the most important chemical is clothianidin, a neonicotinoid insecticide.

3.2. *Contributions of variations in yield and input values to the IYR*

Visualising the contributions of yield and inputs to variation in the IYR shows that yields are less variable than the input values, with the conclusion that the majority of variation in IYR is driven by variation in inputs and their associated risks (Fig. 3). These plots also suggest that generally IYRs are higher for pesticide (Fig. 3a-b) than for fertiliser inputs (Fig. 3c-d). This finding reflects the fact that almost all locations have pesticide input values which are at least half of the maximum

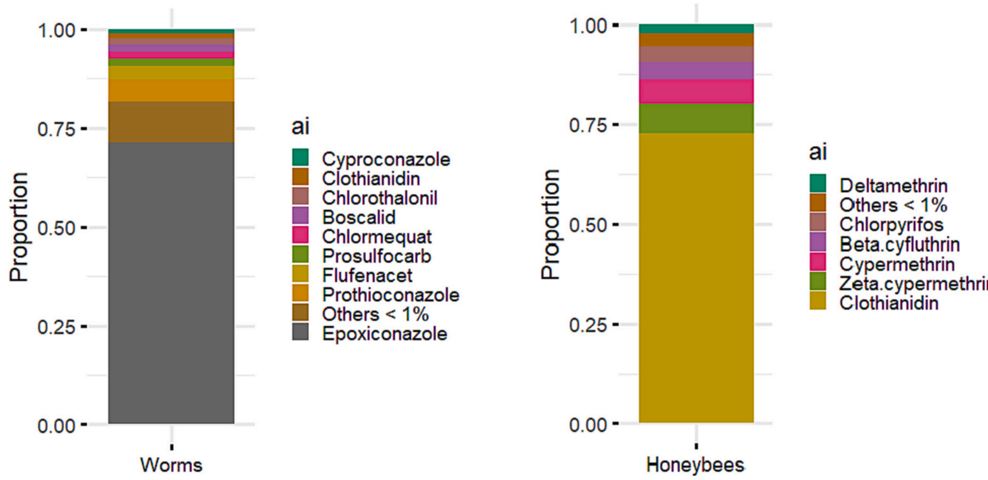

Fig. 2. The pesticide active ingredients contributing the most to potential risk to earthworms and honeybees across English winter wheat crops, calculated as the proportion of potential harm (mixture risk quotient) contributed by each active ingredient (ai).

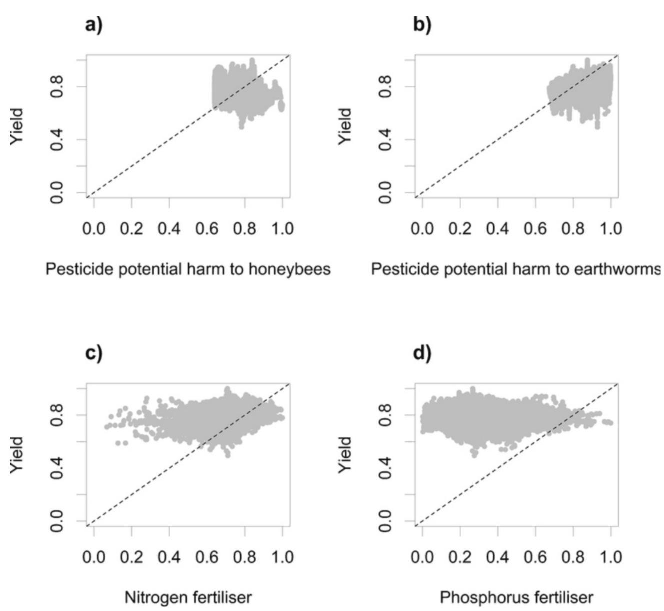

Fig. 3. The patterns of relationships between each of the four agrochemical input types and winter wheat yield. Points are individual 1 km grid cells, and the 1-to-1 line is to aid interpretation. All values are scaled by dividing by the maximum value.

whereas there is much greater variation in fertiliser inputs.

3.3. Areas of overlapping high IYR values do not map well onto low quality agricultural land

We mapped the grid cells which were in the top 25th or 50th percentiles for all four IYR types together, to indicate regions where all agrochemical inputs are high relative to the yields obtained (Fig. 4). These high IYR cells show some geographic patterning, being located mostly in central and south-eastern England.

We also determined whether these areas of multiple high IYR reflect standard classifications of low-quality agricultural land, using the Agricultural Land Classification (ALC). The distribution of ALC grades between the 'high IYR' and 'low IYR' cells is generally very similar, meaning one could not reliably predict high or low combined IYR from ALC or vice versa (Fig. 5). The IYR for pesticide input risks to bees shows some indication that lower IYR cells are more likely to have higher ALC grades, while the lower N and P input IYR cells fall in a slightly higher proportion of best quality Grade 1 land. But there is no clear preponderance of high IYR cells being in poor ALC classes.

4. Discussion

The Input Yield Ratio provides a framework to consider where wheat farming may be less sustainable by expressing the relative balance of inputs of agrochemicals against the crop yield obtained. The IYR patterns are not linked to a standard classification of the quality of land for farming (the ALC), suggesting it reflects other biophysical and social drivers of both yield and use of agrochemicals. The IYR is not a metric for predicting yield from inputs, but rather shows how the balance of inputs to yield varies due, as we discuss below, to a range of drivers.

Wheat is the staple food of temperate regions, so targeting this for our IYR calculations may seem contentious. However, it has been estimated that in the UK and the European Union around 60 % (68.7 Mha) of cropland is used to produce food for livestock, and this share of cropland feeding livestock is larger than the global average (~40 %) (Sun et al., 2022). Consequently, transforming agriculture needs to include changing the farming of wheat both to be more sustainable and to assess where might be given up for restoration or rewilding.

4.1. Implications of spatial variation in IYR

The IYR is calculated at the 1 km grid cell resolution but, because the area of wheat grown varies from cell-to-cell, the IYR is best considered as the estimated inputs relative to yield of a field of wheat grown in that cell. As such, the IYR relates to farm-level decisions. When compared to all wheat growing areas, wheat fields in cells with a low IYR value either have relatively lower demand for agrochemical inputs or greater efficiency of use. A high value of IYR indicates where the agrochemical inputs are high in relation to the yield compared with all other wheat growing areas. This high ratio might be because the use of a pesticide is not warranted by the pest pressure (or has low effectiveness because of pesticide resistance) or that supra-optimal rates of fertiliser are applied; with both issues being commonly reported (Ahmed et al., 2017; Ghimire and Woodward, 2013; Lechenet et al., 2017). A high IYR may also arise if yields are constrained by other factors not considered here, such as limitations in the supply of other macro- and micro-nutrients, or water availability.

We found that the spatial patterns of the four different IYR types vary, and this is driven primarily by differences in the patterns of different agrochemical use across England, rather than variations in yields. This might reflect that agrochemical inputs are likely to be

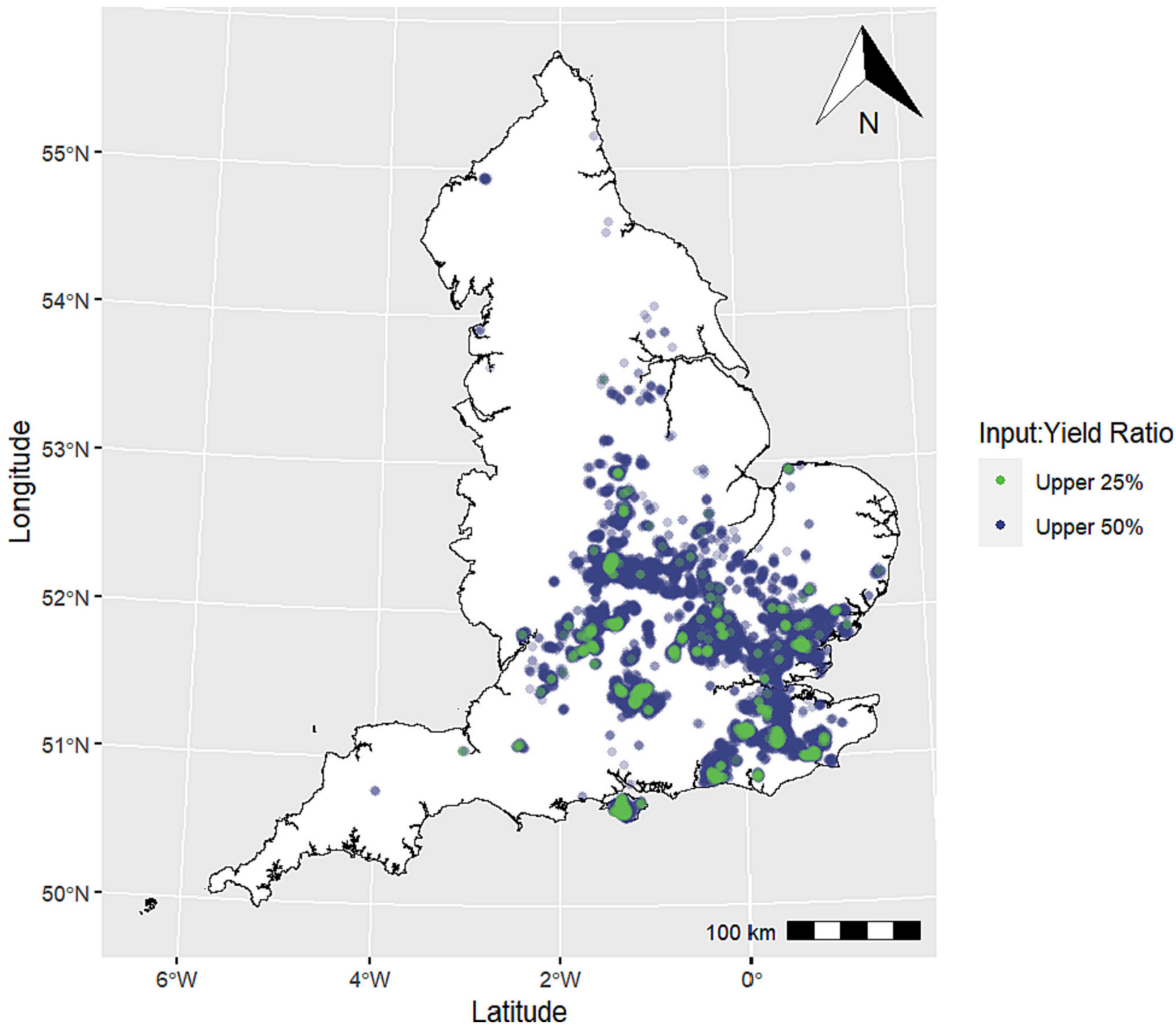

Fig. 4. A map of England showing the 1 km grid cells (enlarged for display, with larger and/or more intensely coloured spots indicating multiple overlapping cells) in the top 25th or 50th percentiles for all four IYR types, showing the locations of highest combined agrochemical inputs compared to the winter wheat yield obtained.

modified by the farmer precisely to optimise yield (Cook and Bramley, 2000), so yield is relatively less variable spatially compared to that of the agrochemicals used. We also show that clusters of cells where IYR is high for all inputs are not those classified as having low agricultural quality by a traditional metric, the Agricultural Land Classification. Therefore, the IYR is identifying patterns in the relative benefits and risks of agriculture which are largely independent of existing classifications. This suggests that farmers in marginal areas are not generally chasing unobtainable yields by applying excess agrochemical inputs. One might expect that where inputs, and thus economic costs, are high, yet yield, and thus economic returns, are relatively low this would make it less attractive for the farmer to maintain these practices. A frequent complaint is that unsustainable farming practices are supported by agricultural subsidies (Scown et al., 2020). Our finding that areas of high IYR across all input types are largely different to low quality farmland as identified by the ALC might suggest that high IYR is not driven by such subsidies and systems that 'prop up' high input farming on low-grade land. That is, if the 'propping up' argument was true in general we would see that pixels with poor ALC grades have a high IYR because farmers are subsidised to put agrochemicals on farmland that does not benefit from these inputs. Rather IYR is likely more strongly driven by variability in the yield that farmers get for their inputs within intermediate grade land. Of course, from a farmer's point of view, it is presumably worth the relatively high levels of input per unit yield as long as the outcome is financially viable. It is only once we translate these actions into wider environmental risk, and the harm that may result (i.e., externalities), that the trade-off becomes apparent.

Variation in agrochemical inputs likely, in part, reflects variation in biophysical constraints on crop production, such as soil fertility and other aspects of soil health, or the types and numbers of pests attacking the crops. The contrasting large-scale spatial patterns of the honeybee IYR (driven mostly by insecticides) and that for earthworms (driven mostly by fungicides) likely reflects spatial variation in important wheat pest groups in England. However, different wheat pests have complex distributions in England (Hardwick et al., 2001) and exhibit spatial variation in their susceptibility to particular pesticides (Comont et al., 2019), which make it difficult to disentangle the exact drivers of these patterns down to the level of the specific drivers of active ingredient use. The two fertiliser agrochemicals, N and P, would not be expected to show similar patterns, as they are typically applied as separate formulations to wheat. Moreover, a straightforward biophysical explanation for the fertiliser IYR patterns is undermined by the poor linkage to ALC

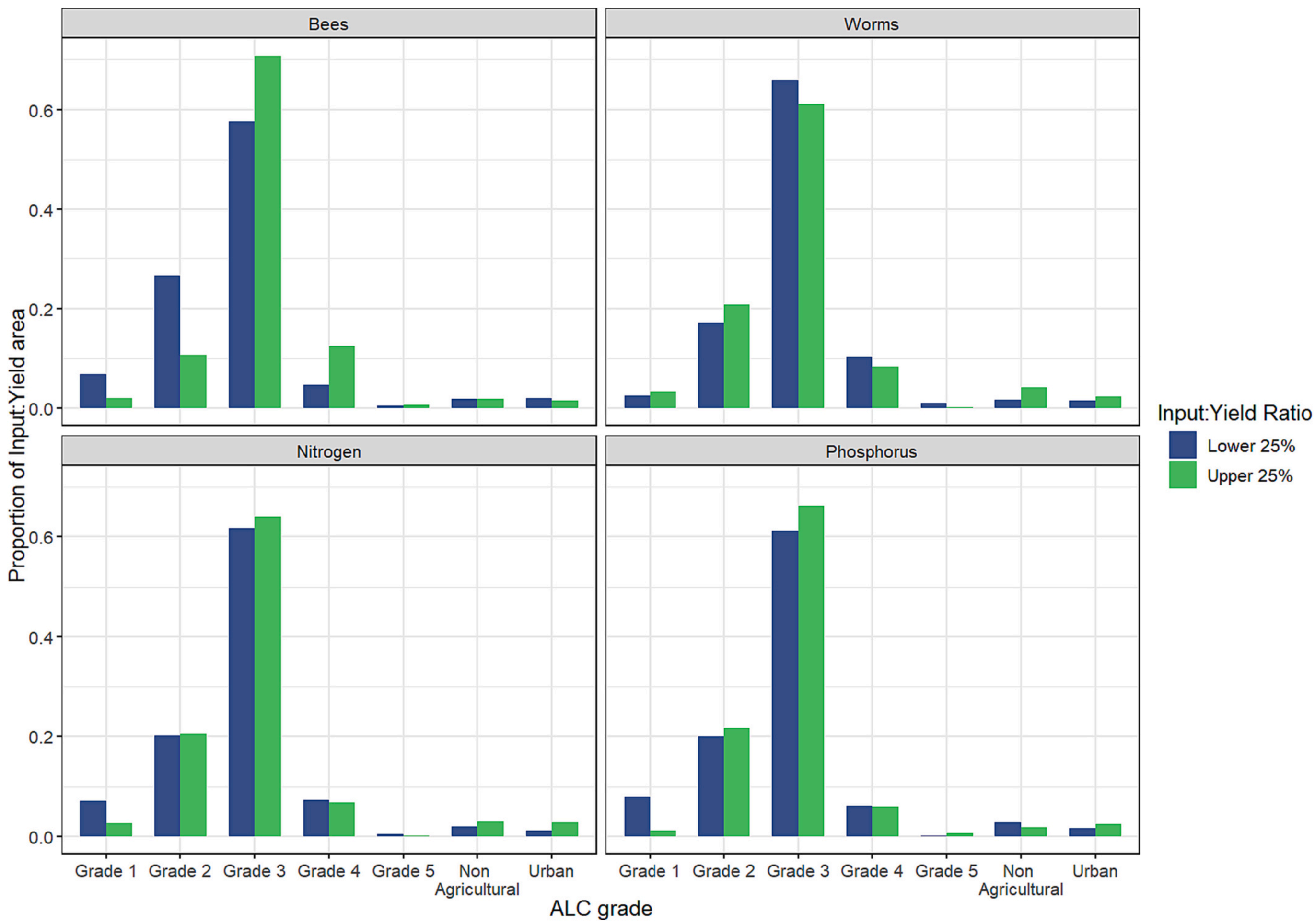

Fig. 5. The proportion of 1 km grid cells in each Agricultural Land Class (ALC) for the grid cells that were in the lowest or the highest 25th percentile for all four agrochemical input types. We used the area of each ALC grade in a 1 km grid cell to determine the dominant ALC grade for that cell. The ALC grades reflect the assessed quality of the land for agriculture: 1 = 'excellent'; 2 = 'very good'; 3 = 'good to moderate'; 4 = 'poor'; and 5 = 'very poor'.

patterns. Spatial variation in IYRs might therefore also reflect a wide range of socio-economic factors, including farm income, farm tenure (e.g., contract farmed or owned), farmer attitude and knowledge and agronomic advice, that are reported to affect patterns of agrochemical use (Bakker et al., 2021; Pedersen et al., 2019; Sharma et al., 2011). Indeed, there is a need for more transdisciplinary research on the combined roles of socio-economic and bio-physical factors in determining agrochemical inputs and impacts (Nkurunziza et al., 2020).

Other causes of variation in IYR might relate to nuances not captured in the data available at the quality and resolution needed for this study. Desired crop quality might be a factor. The highest quality ('Group 1') wheats may receive higher fertiliser inputs to achieve the premium for protein content, and farmers may be willing to spend more on pesticides to protect them. Secondly, in regions with more mixed farming it is likely that the inorganic fertiliser quantified by our data is replaced to an extent by organic manures (Smith and Williams, 2016), so N and P input estimates for these regions could be an underestimate. Indeed, N and P from manures can be a major source of environmental pollution (Smith et al., 2007). However, the N and P application patterns (Figs. A.1, A.2) do not match the large-scale east to west transition to more mixed farming in England (Goodwin et al., 2022). This pattern suggests that the balance of organic to inorganic fertilisers varies mostly at the scale of the individual farm, driven by the quantity, availability and quality of organic manures.

The considerations above in combination suggest that high IYR might be reduced, while still growing wheat, by two complementary approaches that reduce inputs by: i) combatting excess application of agrochemicals through improved information or precision farming techniques (Finger et al., 2019); or ii) reducing the need for inputs by implementing agro-ecological approaches to improve soil health or natural pest control (Wezel et al., 2014). More radical possibilities are to change the crops farmed, to switch to a different farming system such as agro-forestry, or to take the land out of farming completely. Calculating IYR at this time simply provides a framework to understand where the agricultural system appears to have low input for the yield obtained. Understanding the specific causes of these problems and developing workable solutions requires more research. But taking land out of production is certainly possible if our food systems are over-hauled to increase efficiency and sustainability (Dimbleby, 2021).

4.2. Extending the IYR approach

The IYR approach makes an implicit assumption that more agrochemical input results in more *potential* environmental risk. The *realised* harm linked to this risk will be influenced by processes such as agrochemical residence times on the crop and in the soil, uptake of fertilisers by the crop, amount transported in runoff, and rate of pesticide breakdown. These processes will in turn be affected by variables including climate, topography and soil type and condition, as well as when and how agrochemicals are applied, and in what formulations (Farha et al., 2016; Kleinman et al., 2011). Furthermore, the ultimate environmental impact of a particular input of fertiliser or pesticide active ingredient in a location will depend on the species and ecosystems at that location. It might be possible to translate potential risk into realised harm, as knowledge increases on the precise impacts of such variables and processes in such a way as to be accounted for over large areas such as England, rather than at field level. This might allow more direct calculation of a cost:benefit ratio equivalent, if inputs can be robustly translated into environmental costs as a direct result of harm. It is worth reiterating here that farmers do not seem on the whole to be fine-tuning agrochemical inputs in relation to the crop needs, but there is a large degree of variation that might be ascribed to cultural, social, and economic drivers (Nkurunziza et al., 2020; Zhang et al., 2015).

The exact nature of pesticide risk is driven to a large extent by the driving data from hazard assessments. In many cases the available data on pesticide hazards to taxa are limited, but understanding of pesticide impacts on key taxa is improving all the time (e.g. (Bart et al., 2019)). This better knowledge can be used to refine hazard estimates, and any new data from regulatory or research studies that becomes available might change the assessment. Partly for this reason and in line with considering these risk as 'potential', we have simply treated them as having a linear dose response rather than showing non-linear relationships. But, as knowledge increases, especially of accelerating increases in impacts at higher doses, non-linearities could be included.

An important element missing from the current IYR maps is an assessment of uncertainty around IYR values. Calculating an uncertainty that correctly propagates uncertainty from the multiple input layers is challenging but should be a priority for future work.

The IYR framework could be applied across multiple other potentially harmful activities or benefits other than yield, as well as diverse metrics. For example, pesticide impacts could be extended to other indicator taxa, such as freshwater biota (Rumschlag et al., 2020). This would help address a drawback with our study that we focussed on two very well studied species, but which are better adapted to intensively used landscapes than most wild species. Furthermore, one could extend the approach to other crops or even other forms of farming, especially if the multiple types of environmental harm caused by farming are considered; for example, soil erosion, flood exacerbation, or greenhouse gas emissions (Bullock et al., 2021). As we have shown, IYR patterns and values are strongly dependent on the type of input or activity considered, and it is important to consider this variation among types. However, our method of selecting cells where IYR values for all inputs/activities are in the top 25th percentile allows for a simple integrated assessment of areas where agricultural systems are least sustainable. The set of cells will change if more inputs/activities are added, but only insofar as the new set will be a subset of the original set, which allows for consistency as the approach is extended.

We have highlighted the quality of the English data, which allowed us to calculate the IYR for multiple inputs at fine resolution. But similar data do exist for other locations and could provide a basis for IYR calculations beyond England. For example, Denmark and California have databases on pesticide usage (Mancini et al., 2020), a global map of pesticide pollution at ca. 10 km resolution is available (Tang et al., 2021), fertiliser inputs of N and P have been modelled at 30 m resolution across the US Great Lakes (Hamlin et al., 2020), and a global wheat yield dataset at 4 km resolution has recently been published (Luo et al., 2022).

4.3. Conclusions

Transforming the food system towards sustainability ultimately requires a great reduction in the environmental damage caused by intensive farming while producing sufficient high-quality food for people. Managing the tension between reducing harm while producing enough food requires spatial targeting of actions that takes a holistic account of the multiple forms of harm caused by agriculture. By showing large variation in wheat yields and the agrochemical inputs used to achieve these yields, our study presents a supplementary approach to targeting farmland areas where agriculture is more damaging to the environment. To decrease the potential harm from the high inputs relative to yield in these areas, alternative farming approaches or land uses could be explored.

CRediT authorship contribution statement

JMB conceived of the study, led on the research, and wrote the paper. SGJ and WNWF carried out data analysis, made the figures and contributed to writing and editing. HR, CS and DJS also carried out data analysis and contributed to writing and editing. JWR, JS and RFP contributed to development of the study and to writing and editing. All authors contributed to the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The IYR data for each 1 km grid cell are deposited in the UK Environmental Informatics Data Centre at https://catalogue.ceh.ac.uk/documents/dfe2a4a5-2b3a-4731-ba7f-aea7e926f1dd.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.168491.

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