APPLICATION OF THE DANISH PESTICIDE LOAD INDICATOR TO UK ARABLE AGRICULTURE

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Abbreviations:

PLI	Pesticide Load indicator
PPDB	Pesticide Properties Database
PUS	UK Pesticide Usage Survey

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Core ideas:

- The Danish Pesticide Load Indicator is sensitive to UK regulatory interventions.
- Minimal change in the PLI was seen between 2016 and 2018 but regional differences noted.
- Results show a PLI decline associated with the use of insecticides between 2016 and 2018.
- Issues relating to data confidence and linearity of the indicator are highlighted.

ABSTRACT

Pesticides are an important component of worldwide agriculture systems and have contributed to significant increases in crop quality and yields, and so food security. However, despite their societal benefits, pesticides can be hazardous to both humans and the environment. Therefore, effective pesticide polices are needed that balance the societal and economic benefits with the unintentional and undesirable environmental and health impacts. As a result, there has been consistent policy interest in pragmatic and practical techniques that are suitable for assessing the environmental and human health implications of agricultural pesticide use from a national perspective, for assisting in the development of policy initiatives and for communicating policy outcomes to the public. The work described herein aimed to explore the appropriateness of the Danish Pesticide Load Indictor for assessing agricultural pesticides applied in the United Kingdom from 2016 and 2018. In summary, the findings for the two datasets appear broadly comparable, suggesting that the overall environmental load from pesticides on the UK environment remained relatively constant during this period. Regional differences in environmental load and the major contributing substances were identified. Where large differences between the two years were seen, regulatory interventions appear to have been the cause. Overall, the indicator behaves as would be expected and it does appear to be sufficiently, responsive to changes in pesticide use. However, various concerns were identified that may lead to modifications in

how the indicator is calculated and what parameters are included such that it is better able to deliver UK policy objectives.

INTRODUCTION

Pesticides are an important component of worldwide agriculture systems and have contributed to significant increases in crop quality and yields. According to the Food and Agricultural Organisation (FAO, 2020) the production of major crops has more than tripled since 1960, largely due to pesticides and so these chemicals have improved food security and the viability of farming businesses (Cooper & Dobson, 2007; Verger & Boobis, 2013). However, despite their societal benefits pesticides can be hazardous to both humans and the environment. Within the agricultural situation pesticides tend to be applied over large areas of land and, thus, have the potential to disperse in the environment and so contaminate non-target areas and poison non-target species. The consequences are well documented (Bourguet & Guillemaud, 2016; Kim *et al*., 2017; Lee *et al*., 2019; Sánchez-Bayo & Wyckhuys, 2019; Dereumeaux *et al*., 2020; Sud, 2020) and therefore effective pesticide regulatory processes and sound policies are needed that balance the societal and economic benefits with the unintentional and undesirable environmental and health impacts.

To facilitate risk mitigation, the nature of risks themselves in terms of their occurrence, severity and location need to be understood. However, the factors that affect these issues are multiple and highly varied including the physicochemical properties of the active substance (such as its rate of degradation, its mobility, solubility and volatility) and its toxicity to non-target biodiversity. In addition, the active substance formulation, application method, timing and dosage, as well as the environmental conditions (including soil characteristics, weather, and topography) are all important. Therefore, risks arising for a specific active substance are location-specific as well as species-specific making it extremely difficult to accurately quantify these risks from a regulatory perspective. Within the European Union several standard scenarios (e.g. Centofanti *et al*., 2008; Pereira *et al*., 2017), known as the FOCUS (the FOrum for the Co-ordination of pesticide fate models and their Use) scenarios are used to evaluate risks to specific environmental compartments (e.g. surface water, groundwater) using regulatory approved and validated mathematical models. There are many such models, for example, PEARL, the model for Pesticide Emission Assessment at Regional and Local scales, describes the fate of a pesticide in the soil-plant system (Tiktac *et al*., 2012). PELMO, the Pesticide Leaching Model, simulates the vertical movement of pesticides in soil and can be used to predict pesticide leaching (Klein *et al*., 1997). PRZM, the Pesticide Root Zone Model, is often used to predict runoff from agricultural fields (Marin-Benito *et al*., 2020). Whilst MACRO is a preferential flow model used to assess pesticide leaching and drainage (Marin-Benito *et al*., 2020; Nolan *et al*., 2008). There are also other models used to consider wider concerns. For example, PRIMo is the European Food Safety Authority pesticide residue intake model used to perform dietary risk assessment for pesticide residues (EFSA *et al*., 2018). Whilst the GLEAMS model simulates different management systems including crop rotations, tillage practices, conservation practices, irrigation, drainage, fertiliser practices, and pesticide treatments, amongst others (Leonard *et al*., 1995; Rekolainen *et al*., 2000).

Whilst these models are undoubtedly invaluable for pesticide regulation, they are less useful for assessing the environmental and human health implications of pesticide use from a national perspective, for devising policy initiatives or for communicating policy outcomes to the public. These types of models tend to consider the risks arising from of a single pesticide applied to a specific crop rather than the multitude applied across a nation and do not consider the scale of use; both issues being highly pertinent from a policy perspective. Consequently, there has been consistent policy interest in the development of more appropriate techniques for evaluating and monitoring the potential non-target effects to enable temporal trends to be identified. Establishing policies which promote a reduction in the impacts of pesticides is far from straightforward and there are many challenges for the development of these types of tools. Not only do they need to be reflective of the differences between the multitude of pesticide active substances available in terms of their environmental and human health impacts, and be sensitive to changes in the quantities applied, they also need to account for the diverse and ever-changing composition of pesticides being applied; this being due to the development of new active substances and regulatory changes such as the removal from the market of older active substances with known harmful impacts (Milner & Boyd, 2017; Schäfer *et al*., 2019).

To assess the multi-dimensional risks around pesticide usage in a consistent, all-be-it simplified manner, a variety of indicator frameworks have been developed, some of which are hazard based whilst others attempt to consider risk. One of the earliest and simplest but perhaps the most used to-date, is the pesticide Environmental Impact Quotient - EIQ (Kovach *et al., 1992*). This hazard-based indicator uses a scoring approach to determine the effect of pesticides on humans, groundwater and biodiversity. It has been applied to a range of different applications including cropping (Gallivan *et al*., 2001; Kromann *et al*., 2011; Cross *et al*., 2006; Kleter *et al*., 2007), comparing the impact of different herbicides (Kniss & Coburn, 2015) and tomato processing (Bues *et al*., 2004). Another well cited approach is the Environmental Yardstick for Pesticides which quantifies the risks of pesticide use at field, regional and national level. For each active substance the yardstick allocates environmental impact points for the risk to groundwater, aquatic species and soil organisms (Reus *et al*., 2000, 2002; Bressers, 2014). In support of the pesticide reduction program of Flanders, Belgium, the Pesticide Occupational and Environmental Risk indicator, POCER, was developed

(Vercruysse & Steurbaut, 2002; Claeys *et al*., 2005). This is comprised of several modules reflecting the risk to humans from occupational, non-dietary exposure and the risk to the environment. In Germany the SYNOPS indicator (Strassemeyer & Gutsche, 2010; Strassemeyer *et al*., 2017) supports the National Action Plan on the Sustainable Use of Plant Protection Products (a requirement under EU Directive 2009/128/EC which aims to achieve more sustainable pesticides use across the EU) and assesses the acute and chronic pesticide risks to soil, surface water, groundwater and pollinators. Many other indicators have also been developed to support national pesticide risk reduction programs (e.g. Tsaboula *et al*., 2016; Trevisan *et al*., 2009; Kookana *et al*., 2005; Dosemeci *et al*., 2002).

Perhaps two of the most notable indicators from a policy perspective are those of Norway and Denmark with both forming the basis of a national pesticide tax system (Sud, 2020; Böcker & Finger, 2016; Finger *et al*., 2017). The Norwegian system (Spikkerud, 2005) is based on a 'Cumulative Environmental Index' across all pesticide active substances used in the country annually to demonstrate the change in risk over time. It considers various physicochemical and fate properties of the pesticides applied and the ecotoxicity of these pesticides to a variety of terrestrial and aquatic taxa together with a surrogate measure of exposure which is assessed according to the formulation type, the application method, the total application area and a Standard Area Dose (SAD); the latter being set by the national pesticide authority and based on the specific pesticides maximum application rate for each crop it is applied to. The determined risk is then used to place the pesticide product into one of seven bands which each have a set tax rate per treated area. The Danish system is described as an 'environmental load' or pressure indicator (Kudsk *et al.*, 2018; Miljøstyrelsen, 2012). The term 'load' can be ambiguous in the context of assessing the environmental impact of pesticides. The Danish indicator does not try to account for actual harm or damage but aims to reflect, the relative environmental pressure that occurs due to the differing hazardous nature of the pesticides used and the variability in quantities applied. The concept being such that those active substances which are used in large amounts and which are persistent, mobile, bioaccumulate and are ecotoxic to many species should have a higher load than those which are not. The indicator is comprised of three sub-indicators that aim to measure the potential pressure on human health, environmental fate and ecotoxicity. These sub-indicators are then used into two ways. Firstly, to determine the level of taxation and, secondly, combined with national usage data to enable the monitoring of usage trends and environmental load over time.

In contrast to some countries, the UK National Action Plan for the Sustainable Use of Pesticides (NAP; Defra, 2013) has, to date, not made use of an indicator system, such as those described above. Instead, a suite of simpler measures is used to monitor how pesticides are used and the impact they are having. These measures include surveys of pesticide use; results of farm inspections; cropping statistics and rates of adoption and impact of industry initiatives including product stewardship, training and knowledge transfer, as well as monitoring the impacts of pesticide use on human health and the environment (Defra, 2013). The 2013 UK NAP is now being revised with one of several aims being the reduction of risks associated with pesticides by improving metrics and indicators. Hence, a more detailed look at existing pesticide risk indicators and their appropriateness to the UK has been undertaken.

The aim of the study described here was to explore the appropriateness of the Danish approach to the United Kingdom based on pesticide use on arable crops during 2016 and 2018. Selection of the Danish approach for this study was made at the request of the UK policy team, based on the Danish indicators proven track record in pesticide policy (Pendersen *et* *al*., 2015; Sud, 2020), as well as recent evidence of robustness when predicting extreme risks relative to other quantity based indicators (Möhring *et al*., 2019). More complex indicators such as the SYNOPS model or POCER, mentioned previously, have been discussed in a UK context but are reliant on localised data (e.g. relating to weather and soil conditions at the time of application) that cannot be meaningfully aggregated at the national scale for historic UK periods based on existing data collections (de Baan, 2020). By contrast, the structure of the PLI and its close links to existing resources such as the Pesticide Properties Database - PPDB (Lewis *et al*., 2016) means that it can be straightforwardly and transparently adapted to a novel national context with minimal changes or requirements for further large-scale data collection. Other indicators such as the EIQ (Kovach *et al*., 1992) were not seen as offering sufficient breadth in terms of coverage of environmental issues or ability to discriminate between active substances (Kniss & Coburn, 2015).

METHODS

The Danish Pesticide Load Indicator

The calculation of the Danish PLI has been described in detail previously (Kudsk *et al.*, 2018; Miljøstyrelsen, 2012). In summary, a pesticide load (PL) is calculated for three sub-indicators (human health, environmental fate and ecotoxicity) and expressed as the PL per unit of commercial product (e.g. litre, kilogram, standard dose, capsule or tablet). This is shown schematically in Figure 1. The human health indicator focuses largely on operator exposure and is determined by assigning a score between 10 and 100 for the risk phrases for each pesticide active substance (defined according to the Dangerous Substances Directive, 67/548/EEC), with the highest score allocated to those substances most damaging to health. For example, a score of 10 is given if the active substance is a skin irritant or harmful if swallowed but a score of 100 if the active substance is fatal if swallowed or may cause genetic defects. Human health scores are summed and converted to 'pesticide loading points' by dividing the total points by 300. The environmental fate indicator considers soil degradation expressed as the soil half-life (DT_{50}), the SCI-GROW index which is an indicator of mobility and leaching risk (US-EPA, 2007) and bioaccumulation using the bioconcentration factor (BCF). The ecotoxicity sub-indicator is determined using acute and chronic toxicity threshold data (e.g. LD_{50}, LC_{50}, NOEC, LOEC) for a range of species (Figure 1). Data for the fate and ecotoxicity sub-indicators are taken from the PPDB (Lewis *et al*., 2016). The PPDB is a comprehensive relational database of pesticide chemical identity, physicochemical, human health and ecotoxicological data collated from regulatory studies and peer reviewed literature that is maintained by the University of Hertfordshire, UK.

For the environmental fate indicators, the 'raw' data, as extracted from the PPDB, are converted to 'pesticide loading points' by first identifying a reference pesticide, defined as the most harmful active substance for each parameter (e.g. the longest soil half-life) and all other substances are expressed relative to this reference active substance (i.e. the value for the pesticide divided by the value of the reference substance to give a score between 0 and 1). For the ecotoxicity indicators, the process is similar except the reference pesticide is the one with the lowest value (i.e. greatest toxicity) and an inverse relationship is used to derive the loading points (i.e. the load value of the other substances are derived using the equation: 1/(active substance value/reference active substance)). This defines a standardisation 'curve' for each indicator that converts the raw data to an index value. The 'pesticide loading points' for each measure are then determined by multiplying this value by a weighting factor which is essentially the maximum number of PL loading points per unit of commercial product for that particular parameter. As the weighting value varies from parameter to parameter (Figure 1) these weighting values allow issues or policy concerns, such as loss of pollinators or groundwater contamination, to be given greater relative significance within the sub-indicators. The weighting factors are also different depending on whether the product is applied as a field application or as treated seed (Figure 1). Each of the three sub-indicators is expressed as the sum of the weighted values of the underlying measures and given equal significance in the overall PLI.

The final step is to take the pattern of usage into account. In Denmark farmers are obliged to report their pesticide usage for each growing season to authorities. These data are used to estimate a Treatment Frequency Index (TFI) by dividing the total amounts of active substances used in each crop by the standard doses assigned to each use of the active substance (Kudsk, 1989) for the whole country. This data is then combined with the total 'pesticide loading points' to provide an estimate of the pressures placed on the nation from pesticide use.

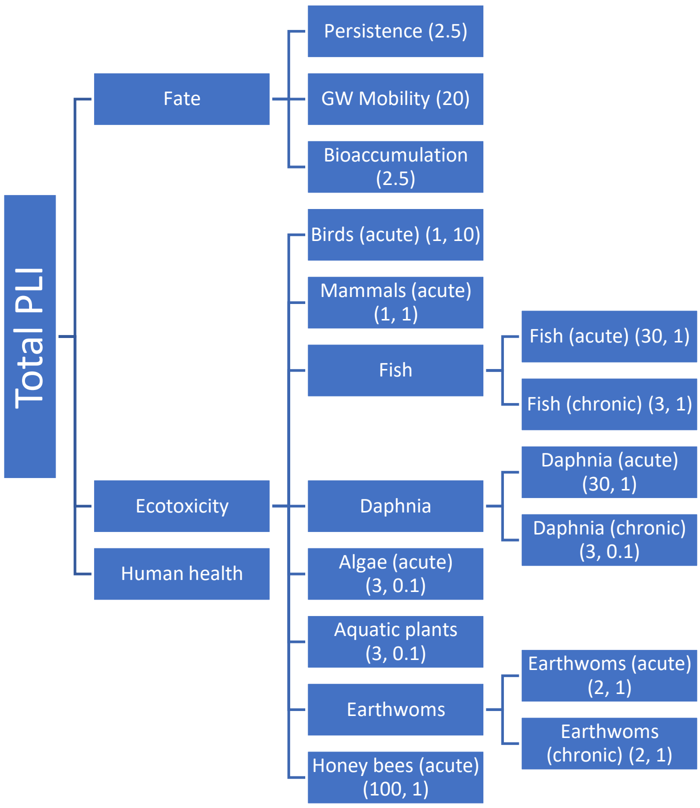

FIGURE 1. Structure of the Danish Pesticide Load Indicator. Values given are numerical constants (weighting factors) used to aggregate standardised values. Where multiple values are listed the second applies to seed treatment, and the first to all other treatments.

Application of the Danish PLI to the UK

For this initial evaluation of the PLI in the UK context it was decided to apply the Danish approach exactly in terms of input parameters and weightings to arable production in the UK. Consequently, the first stage of this work was to identify the pesticides used in this context. The parameters used and the identified reference active substances are shown in Table 1.

In contrast to Denmark, UK farmers are not required to report their pesticide usage to authorities. Instead, biennial agricultural, horticultural and four yearly grassland, fodder and amenity pesticide usage surveys (PUSs) are conducted for a representative sub-set of holdings to estimate the mass of individual actives applied within regions of the UK (Thomas, 2001). These data (in their aggregated form) are accredited National Statistics and can be accessed from the UK public repository (Fera, 2021). A list of pesticides used, both as sprays and seed treatments, were extracted from the two most recently published arable surveys, 2016 and 2018 (Garthwaite *et al*., 2018; 2019). For each of the pesticides identified from the surveys, data were extracted from the PPDB (Lewis *et al*., 2016) and the reference active substance identified (Table 1). For each parameter, missing data were given default values based on a 'reasonable worse case' taken as the 95th percentile (or 5th percentile for ecotoxicity where the lower the value the more toxic the substance) of all data for that parameter. Active substances with a soil degradation time of less than one day were represented as the weighted sum of the properties of their major metabolites, based on the formation fraction listed in the PPDB (Miljøstyrelsen, 2012).

TABLE 1. Fate and environmental parameters used in the UK Pesticide Load Indicator

Sub-indicator	Parameter	UK Reference substance (value)
Environmental fate		
Soil degradation	Soil half-life (DT_{50} as days)	Diquat (5500 days)
Soil mobility	SCI-GROW: calculated from DT_{50} and the organic-carbon sorption constant (Koc/Kfoc as mL g^{-1})	Flutriafol (5.13)

Bioaccumulation	Bioconcentration Factor (BCF as L kg^{-1})	Pendimethalin (5100 L kg^{-1})
Ecotoxicity		
Birds	Acute LD_{50}	Oxamyl (3.16 mg kg^{-1})
Mammals	Acute oral LD_{50}	Oxamyl (2.5 mg kg^{-1})
Fish	Acute 96 hr LC_{50}	Tefluthrin (0.00006 mg L^{-1})
Fish	Chronic 21 d NOEC	Tefluthrin (0.000004 mg L^{-1})
Daphnia	Acute 48 hr EC_{50}	Tefluthrin (0.00008 mg L^{-1})
Daphnia	Chronic 21 d NOEC	Lambda-cyhalothrin (0.000002 mg L^{-1})
Algae	Acute 72 hr EC_{50}	Picolinafen/Bifenox (0.00018 mg L^{-1})
Aquatic plants	Acute 7 d EC_{50}	Clodinafop-propargyl (0.00019 mg L^{-1})
Earthworms	Acute 14 d LC_{50}	Beta-cyfluthrin (0.565 mg kg^{-1} soil)
Earthworms	Chronic 14 d NOEC	Imazaquin (0.028 mg kg^{-1} soil)
Honeybees	Acute 48 hr LD_{50}	Deltamethrin (0.0015 μg bee^{-1})

To estimate usage in the UK 2016 and 2018 PUS data for arable cropping (Garthwaite *et al*., 2018; 2019) were used to estimate the amount of each active substance applied in each region and standardised holding size group (‘strata’ as defined in Thomas (1999)). PUS data are collected as pesticide application records at field level derived from the recorded rate of application of each product (including seed treatments) and formulation used by a farmer. These data were then used to provide regional estimates of pesticide usage via a conservative bootstrap approximation, wherein the population of un-sampled holdings for each active substance (taken from the Defra ‘June survey’ (Defra, n.d.), and assumed to be known without error) were modelled using random draws of the rates from those holdings sampled during the PUS. The bootstrap is explicitly conservative (in terms of proclivity to underestimate the use of a specific active) in that, where there were no sampled holdings within a strata where a particular active was applied, this was considered insufficient to provide an (implicitly errorless) estimate of the potential usage of that active for that population. In those cases, bootstrap sampling was instead based on a 'conservative reference population', comprising either on all sampled holdings within the region (regardless of size group), or sampled across different regions within each bootstrap replicate (such that every active had a change of a non-zero record of use in the population used to represent the unsampled holdings).

Presented estimates of uncertainty correspond to the cumulative uncertainty on the aggregated value of the indicator given the 95% confidence interval for each active substance on each holding size-group within a region.

RESULTS

As might have been expected due to the relatively short time between the two surveys, when the overall regional UK PLI values are calculated there is limited evidence for significant differences between estimates for 2016 and 2018. As shown in Figure 2, the estimates of application mass across all pesticides combined are quite similar for the two years and are within the estimated margin of uncertainty for all regions.

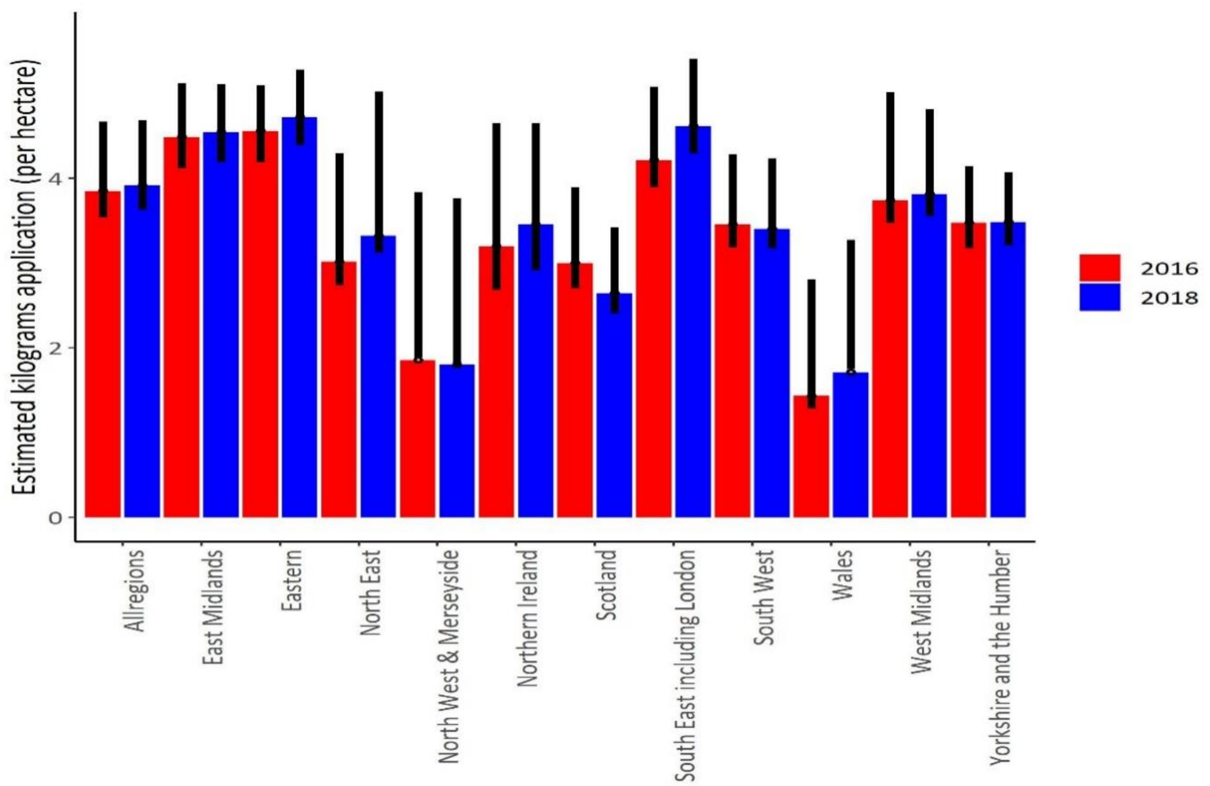

FIGURE 2. Estimated raw mass of pesticide application in kg per hectare for the different UK regions for the two case study years. Confidence limits (95%) are based on the cumulative estimate of the conservative bootstrap of mass of application based on data from the UK PUS**.**

Estimates of regional variation in the value of UK PLI are largely in line with the mass of pesticide application, with the highest overall loadings associated with the more intensively farmed East Midlands and Eastern regions (Figure 3).

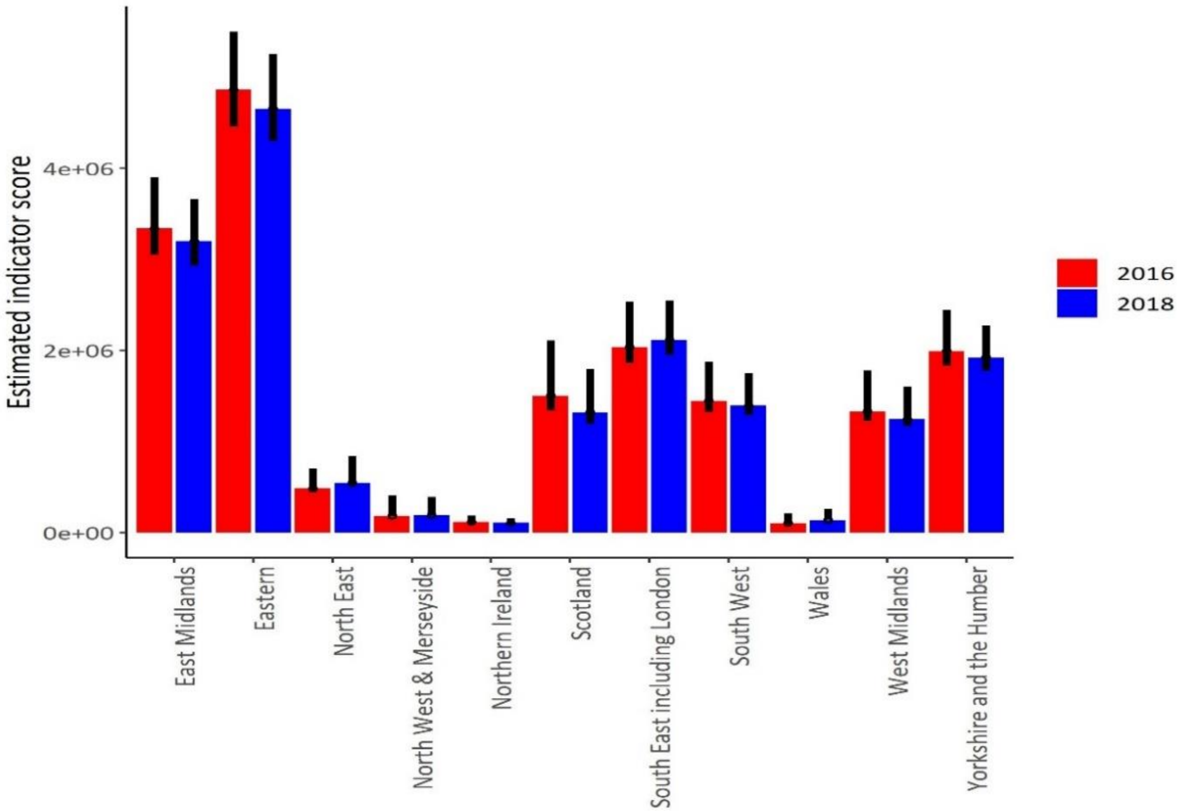

FIGURE 3. Total calculated UK PLI per UK region for arable cropping in 2016 and 2018. Confidence limits (95%) are based on the cumulative estimate of the conservative bootstrap of mass of application based on data from the UK PUS multiplied by total 'pesticide loading points' for each substance across all measures.

Figure 4 provides a breakdown of the contribution of different pesticide groups to the components of the indicator when aggregated nationally. Herbicides are the most important group overall (comprising 78% of the overall value in 2016) in determining the value of the UK PLI, followed by fungicides and insecticides. This pattern was also observed within the majority of years in Denmark (Miljøstyrelsen, 2012).

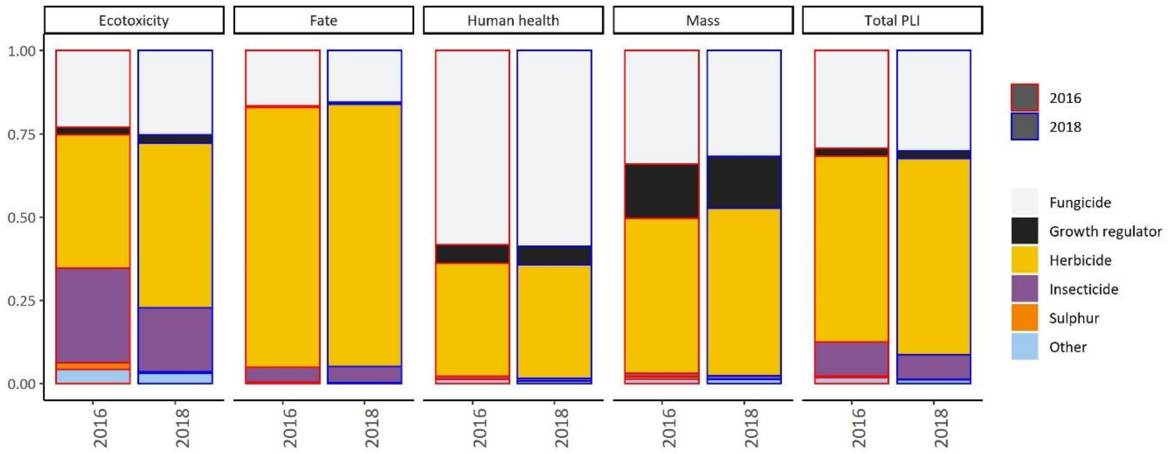

FIGURE 4. Contribution of pesticide groups to the value of the UK PLI across years. Values are given at the mean estimate of the mass applied.

Insecticides are the group which makes the largest contribution to the indicator calculation relative to their mass of application and is the group undergoing the largest change between the two years sampled. In both datasets, insecticides make up approximately 1% of the mass of pesticide application but their contribution to the UK PLI value ranges from between approximately 10% and 7% for 2016 and 2018 respectively. Given their reason for use it is unsurprising that the component most impacted by insecticides is the environmental toxicity (Figure 4 - Ecotoxicology), which shows a notable decline in both the total value (4,260,723 PLI units in 2018 compared to 4,883,026 PLI units in 2016) and in the contribution of insecticides (28.4% in 2016 compared to 19.1% in 2018). This suggests a decline in the hazard associated with the use of insecticides between the two surveys.

Fungicides are most significant for their contribution to the human health component of the index, wherein they comprise over half of the load associated with operator exposure. Beyond reinforcing the significance of fungicides when considering mitigation of operator exposure (particularly given the increasing importance of tank mixing as a technique for combating development of resistance) there is limited evidence for major changes in fungicide application or loading observed between the two surveys.

Most of the minor components contributing to the UK PLI show patterns of change largely in proportion to their mass of application, suggesting minimal shifts in the relative loading associated with the composition of active substances in use. Interesting patterns can be observed with respect to molluscicides, in that an increase in overall application mass in 2018 is not associated with any notable increase in contribution to the UK PLI. In-depth investigations indicate this may be associated with a shift in compound use away from the high impact actives such as metaldehyde, and towards lower impact alternatives, notably ferric phosphate.

Identifying the specific active substances responsible for driving the changes in the UK PLI showed that among the major contributors (here defined as any active substance which individually contribute >= 20% to the UK PLI or any of its sub-indicators), the largest absolute changes between 2016 and 2018 are associated with declines in the application of chlorpyrifos and cypermethrin, additional to a smaller scale increase in the application of clothianidin seed treatments (Figure 5). Chlorpyrifos is an organophosphate compound with long standing concerns over toxicity to humans, bees and aquatic invertebrates (e.g. Rauh *et al.*, 2012). The majority of products containing this compound were officially withdrawn for use within the UK in 2016, which was therefore the last year where wide-scale use of chlorpyrifos would be expected to be observed within the PUS, providing evidence that the PLI as defined is sensitive to the withdrawal of a high impact active substance.

Cypermethrin is a non-systemic pyrethroid which remains authorised for use in the UK on a wide range of agricultural crops as well as in veterinary medicine. Declines in cypermethrin usage are possibly related to substitution with the synthetic pyrethroid lambda-cyhalothrin, as well as shifts in the isomer used to favour the more rapidly acting zeta-cypermethrin.

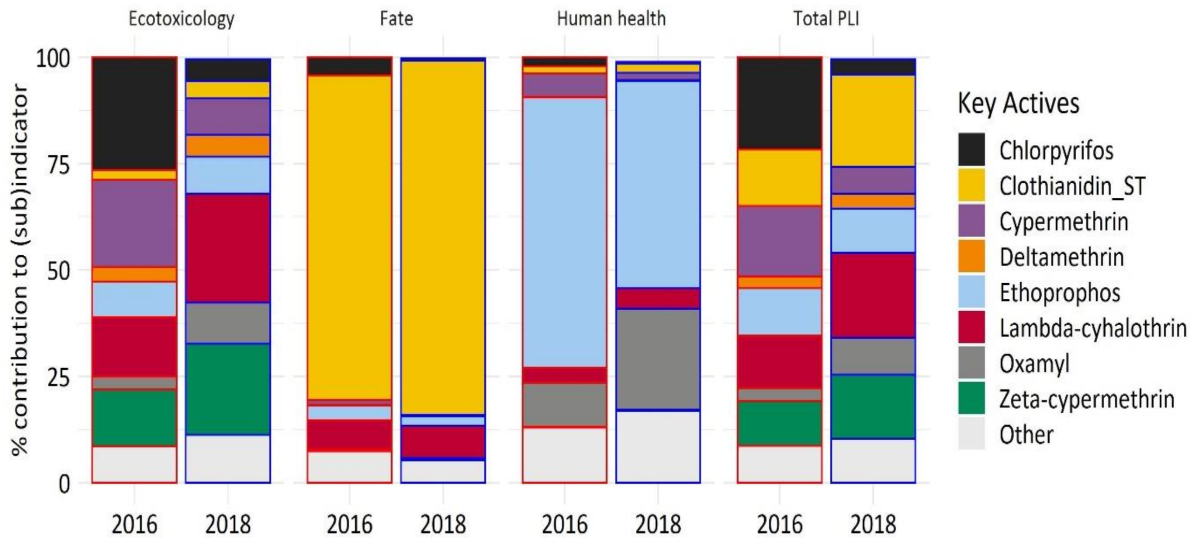

FIGURE 5. Contribution of individual insecticides to the UK PLI within this chemical group. Values are given at the mean estimate of the mass applied.

As can also be seen in Figure 5, the only insecticide to show significant increases in overall usage between the two years is the neonicotinoid clothianidin when used as a seed treatment. This was mainly for wheat and to a lesser degree was also used with oilseed rape (2016 only), sugar beet and other winter cereals. There has been considerable controversy in recent years around the use of neonicotinoids particularly with respect to impacts on pollinators (Lu *et al*., 2020; Osterman *et al*., 2019) and UK guidance now prohibits the outdoor use of clothianidin. Longer term trends in neonicotinoid usage in the UK suggest a gradual increase in clothianidin usage since 2000 (Budge *et al*., 2015) but it is unclear from the 2016 and 2018 data what precise impact the change in regulations have had.

The carbamate insecticide oxamyl is used for the control of various soil-based invertebrates and nematodes, particularly on potatoes and sugar beet. An increase in contribution to the UK PLI can be seen in Figure 5 when comparing the data for the two surveys. However, data for the West Midlands region (Figure 6), a region subject to an overall significant change in UK PLI value (Figure 2), shows a significant decrease in the contribution of oxamyl to the indicator value suggesting that the overall patterns of change in the PLI are best understood at a regional level. Oxamyl was withdrawn from use on most arable crops in the UK in 2020. Lambda-cyhalothrin was also identified as undergoing inconsistent patterns of change across regions. This complex pattern of change highlights one of the key challenges facing the indicator approach as implemented as a policy tool, in that by nature a single indicator aggregates over a wide range of different and potentially conflicting changes within the composition of pesticide usage. Understanding this underlying complexity is particularly important where the goal is to support intervention.

Ethoprophos is a soil incorporated insecticide used to control wireworm and potato cyst nematode infestations. It is considered to be an acetylcholinesterase inhibitor and may also be genotoxic (EFSA, 2018). Hence, as may be expected, it has a relatively high human health contribution to the UK PLI. A notable decline in usage is seen between 2016 and 2018. Whilst important for the human health component in both years, the decline in 2018 changed the contribution to the overall UK PLI only slightly. Ethoprophos no longer has approval for use in the UK having been withdrawn in 2019.

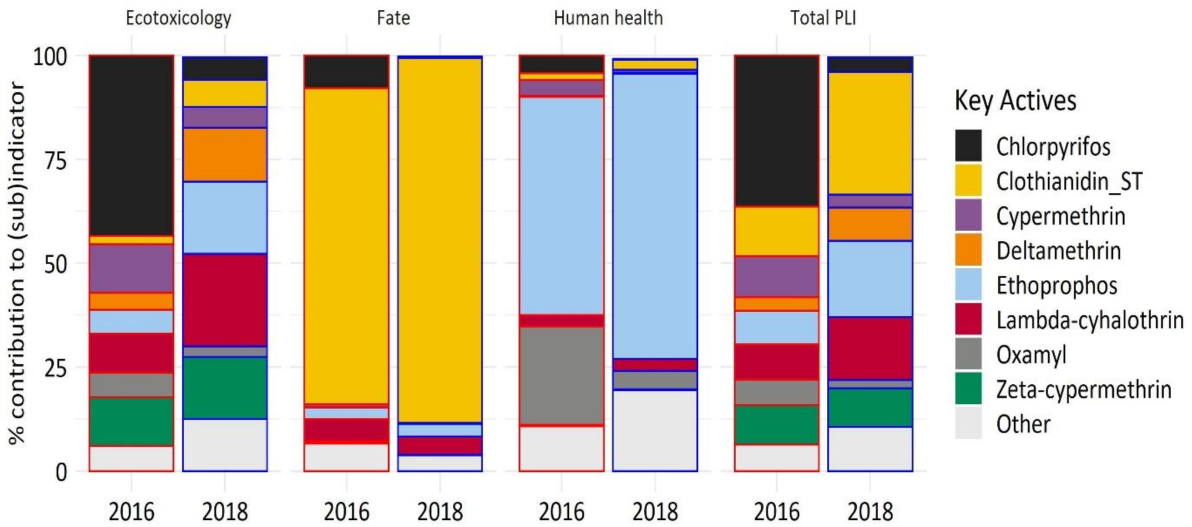

FIGURE 6. Contribution of individual insecticides to the UK PLI sub-indictors and the total. Values are given at the mean estimate of the mass applied.

DISCUSSION

Broadly speaking the calculated UK PLI behaves as would be expected and provides a good visual representation of the impacts of arable agricultural use. When comparing the two datasets, reasonable explanations were evident when significant changes in the indicator value were seen. However, several observations were made during the study which highlighted issues of concern which may mean modifications to the Danish methodology are required if it is to be used in the UK policy context.

A key challenge is ensuring the UK PLI is suited to the UK geological and hydrological landscape. The Danish PLI is heavily focused on the protection of groundwater which reflects the fact that more than 99% of water use in Denmark has groundwater as its source (Jørgensen & Stockmarr, 2009) – hence the use of the SCI-GROW parameter. However, in the UK surface water is the main (~68%) source of tap water with only about a third being extracted from groundwater with this value being much less in Scotland (3%) and in Northern Ireland (6%) (Water UK, 2021). Consequently, some rebalancing in favour of protecting surface water quality may be required within the UK PLI. There is also an issue with the SCI-GROW calculation in that data are sometimes not available to facilitate the calculation meaning that a default is used and thus uncertainty is created. The Groundwater Ubiquity Score (GUS) index (Gustafson, 1989) may be a potential alternative to SCI-GROW as there are fewer substances for which GUS cannot be calculated.

Resolving the implications of uncertainty within the index is a further challenge for the UK PLI. Care needs to be taken to ensure that uncertainty is appropriately represented, particularly given their comparatively large size relative to the observed trends between years. Whilst the principal source of the observed uncertainties is related to the need to estimate usage overall based on the finite sample of holdings recorded as part of the UK PUS, there are also concerns around parameter uncertainty. Some of the parameters, for example soil half-life (DT_{50}) and soil adsorption coefficient (koc/kfoc) are both known to vary substantially. The values held within the PPDB and used here (Lewis *et al*., 2016) are the geometric mean estimated across all available experimental data. For many active substances there are data for a comprehensive range of soils but for others the parameter value may be based on just one or two soil types and so may not be truly representative. Improving the data, how it is handled and/or determining a measure of uncertainty may be needed.

Other issues that were noted included the lack of chronic toxicity data for mammals and birds within the Danish PLI. At the time the Danish PLI was first established these data were not included within the PPDB and as no alternative suitable data source was found these parameters were excluded from the Danish PLI. However, these parameters have now been added to the PPDB and so could quite easily be added to the indicator. Whilst it would be desirable to also include chronic toxicity data for earthworms and wild bees (e.g. bumble bees and solitary bees) insufficient data are available in either regulatory documents or peer reviewed literature to make this exercise worthwhile although it is expected that this issue will resolve in time as more data are generated for regulatory purposes (Lewis & Tzilivakis, 2019).

One area where a potential solution is yet to be identified is the lack of coverage of the risks to consumers. Whilst the inherent toxicological properties of pesticides are the same regardless of the receptor, using the active substance risk phrases focuses largely on the operator. Consumer risks are not directly covered and are complex in that dietary exposure is dependent on another set of variables such as dietary intake and consumer profile (e.g. age, cultural factors, underlying health issues, preparation/cooking/processing etc.). Dietary risks also need to be combined with the need to consider surface water quality as the major drinking water source in the UK. There is, of course, the argument that as an 'environmental load' consumer impacts are outside of the scope of such an indicator, given that this could implicitly lead to a 'trade off' of human health and environmental concerns (Maud *et al*., 2001), but there is also a counter argument that consumers are the end receptors in the same way as wildlife are exposed when they feed on pesticide treated crops. Resolving this issue, particularly in response to the different systems of regulation around these types of risk in the UK, is an area to be explored in future work.

Finally, a major issue around the calculation of the PLI, albeit one shared with many other pesticide indicator methodologies (Reus *et al*., 2002), is the implied linear relationship between the weighted measures of impact and the mass of pesticide application. Under the current model the overall UK PLI for a given active substance in a region is simply a multiplication of the calculated indicator value and the mass of application, thus a doubling of the application mass has the effect of doubling the indicator value. This procedure has the advantage of transparency, and thus simplicity for policy but does mean that, to varying degrees, certain measures have the potential to be mis-represented in terms of their assumed impact. The extent to which this is a concern for the value of the indicator is dependent on whether in-field application rates lie outside of the effectively linear part of the dose response curve, an issue which may vary between actives.

This linearity also has consequences for the role played by the reference active substances in determining the overall distribution of scores across the set of included pesticides. As reference active substances are those which have the highest potential for impact per kilogram ‘load’ with respect to a specific measure, it follows that the value of this active substance when compared to the remaining distribution can have a significant effect on the relative scoring of active substances, and thus relative contribution of measures, on the overall indicator value. There is also the potential for regulatory change to impact on what is assigned as the reference substance. For example, if diquat were to be withdrawn in the UK its role as the reference active substance for soil degradation is called into question. If a new worse case active substance is then used comparison with previous years would no longer be valid. However, if the original reference active substance is kept and, overtime, other active substances with relatively high loadings are also removed, then the reference active substance becomes more and more extreme thus introducing the potential for distortions in the standardisation 'curve'. This can result in many typical active substances having extremely low score values, resulting in an indicator which disproportionally prioritises a small number of high impact pesticides. For example, diquat has a DT_{50} of 5500 days whereas the median across all active substances is 20 days, and so diquat would be associated with an unweighted score of 1, the median substance would have an unweighted score of 0.064. As another example, an active substance that has a soil DT_{50} of 366 days has a resulting load index of 0.07 but the regulatory interpretation of this value would be that it is very persistent, hence there is a disparity between the load indicator value and the regulatory interpretation of the soil DT_{50}. The extent of deviation between the value of the reference active substance and those of more typical active substances is known to vary across different measures, which has the effect that their relative contribution for typical pesticides may be strongly distorted by the choice of reference substance.

Finding a solution to the issues caused by linearity is not easy but one potential way forward is to introduce 'reference points' into the definition of the standardisation ‘curve’ for each load metric. The reference active substance would still be used but regulatory threshold values could be introduced that set reference points between 1 and 0 to ensure the load metric corresponds with a suitable load value. For example, general interpretation of soil degradation values would consider a soil DT_{50} of <30 days as non-persistent, 30 to 100 days as moderately persistent, 100 to 365 days as persistent and >365 days as very persistent. These thresholds could be set to correspond to load values of 0-0.25, 0.25-0.5, 0.5-0.75 and 0.75 to 1.0. Thus, rather than a straight line between 0 and 5500 days corresponding to a load index of 0 to 1, a series of straight lines define the standardisation ‘curve’, that results in load index values that are more in line with the regulatory interpretation of the metric. Using these thresholds, a soil DT_{50} of 366 days would be given a load index of 0.75 compared to 0.07.

The sensitivity of the Danish PLI methodology when adapted to a novel context can be viewed as the combined impact of missing/estimated data, linearity in response to change, and the manner in in which weighting values are defined. A challenge for conventional sensitivity analysis is that unlike other indicators previously explored in this way, such as PURE (Zhan & Zhung, 2013) and SYNOPS (de Baan, 2020), not all the parameters in the PLI can be said to have a meaningful and objective parameter space over which the performance of the indicator can be assessed (de Baan, 2020). For example, the weighting values defined in Denmark are used here without modification, in part due to a lack of consensus among consulted UK policy makers, as to how to define an appropriate parameter space for those which are inferred to reflect socio-political concern for the various elements of pesticide load (Miljøstyrelsen, 2012; a similar issue also arises when considering how to vary the scores assigned to different risk phrases in the human health component). In the future it may be possible to define a measurable basis for weighting via calculating measures of revealed preference and willingness to pay (e.g. Travisi & Nijkamp, 2008; Travisi *et al*., 2006), although due to the range of potential stakeholders involved, this may raise further political complications relating to the adoption and interpretation of the indicator. In contrast with PURE and SYNOPS the Danish PLI (excluding human health) is a fully linear aggregation, and thus has no expectation of interactions or nonlinear responses among input factors (beyond that defined by the standardisation curve) (Zhan & Zhung, 2013). Intrinsic correlations between underlying indicators may exist and be of interest in certain policy context but are of unclear practical relevance in the scope of a national monitoring tool.

In terms of how the UK PLI could be used in practice, the analysis undertaken focused primarily on its utility as a comparative tool, that is in reflecting differences in the inferred load on ecological and human systems across time and space. This is also reflected in the original development context for the Danish PLI, where the primary aim was differentiating between active substances so that they could be taxed at varying levels. However, the limitations of these types of indicators do need to be understood. Ultimately the validity of any indicator use for comparison or benchmarking is strongly dependent on maintaining a consistent baseline against which to compare change. In the context of the PLI, this baseline depends on a single reference active substance and consistent set of weighting values and these cannot change without recalculating all previous years, and this itself would impact on the indictor transparency. Likewise, as pesticide usage in terms of active substances applied is different in the UK to that of Denmark, the reference active substances are different for the two countries and so the pesticide loadings cannot be compared with other countries or other indicators.

CONCLUSION

The work described herein aimed to explore the appropriateness of the approach used for the Danish pesticide load indictor to agricultural pesticides applied in the United Kingdom, largely for policy purposes. In summary, the indicator values for the 2016 and 2018 datasets appear broadly comparable, suggesting that the overall environmental load from pesticides on the UK environment remained relatively constant during this period. For the differences that were identified, logical reasons were seen which were mainly due to regulatory interventions and the sensitivity of the indicator to such changes was clearly demonstrated. The UK PLI also appears to facilitate transparent communication of the impact of agricultural pesticide use. As noted previously the UK does not currently have a widely recognised policy tool equivalent to the PLI; the role instead being played by a combination of the PUS and more targeted indicators defined under the UK NAP (Defra, 2013). The role the PLI may play in UK policy development remains to be clearly defined, although it is likely that due to differences in the underlying data structures this will be different from that used in Denmark.

Some shortcomings were identified in the PLI-methodology in terms of its practical application and the suitability of the parameters included (or excluded) such that if the decision is taken to utilise the indicator in the UK it is probable that adjustments might be needed to better reflect UK conditions and policy objectives. There may also be the need to resolve, or at least identify a means of communicating, the uncertainties associated with the usage data that in the UK is based on a voluntary PUS from a sub-set of holdings, unlike the statutory obligation on the part of Danish farmers to report their pesticide use to

Government. There is no doubt that solutions still need to be found and research undertaken to show that the changes appropriately reflect the environmental and human health implications of agriculture pesticide use.

This work was undertaken to consider the suitability of the Danish PLI to the UK specifically but there are several observations that might be useful to highlight if a similar approach was to be taken in other countries. The availability of suitable quality data relating to pesticide usage is a critical factor, particularly if regional interpretations are to be made. The greater the uncertainty relating to usage the less reliable the indicator will be at describing trends. The inclusion of data relating to human health also needs careful consideration as it has significant potential to be misinterpreted and/or under-represented due to the absence of a consumer element. In addition, issues relating to linearity and the lack of correlation with regulatory data interpretation is important for transparency. Nevertheless, the Danish Pesticide Load indicator may provide a sound and adaptable starting point for a national pesticide policy indicator.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

AUTHOR CONTRIBUTIONS

This manuscript was written by K. Lewis and J. Rainford with support and input from other authors. The indicator calculation script and statistical analysis was conducted by J. Rainford. Data extraction from the PPDB and its validation was done by K. Lewis and J. Tzilivakis. Data from the PUS was formatted and provided by D. Garthwaite. Technical developments, interpretation and analysis were a shared team responsibility.

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