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# An adaptable integrated modelling platform to support rapidly evolving agricultural and environmental policy

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A R T I C L E I N F O

*Keywords:*
Integrated modelling
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Co-creation
Trust
Transdisciplinarity
Policy support

A B S T R A C T

The utility of integrated models for informing policy has been criticised due to limited stakeholder engagement, model opaqueness, inadequate transparency in assumptions, lack of model flexibility and lack of communication of uncertainty that, together, lead to a lack of trust in model outputs. We address these criticisms by presenting the ERAMMP Integrated Modelling Platform (IMP), developed to support the design of new "business-critical" policies focused on agriculture, land-use and natural resource management. We demonstrate how the long-term (>5 years), iterative, two-way and continuously evolving participatory process led to the co-creation of the IMP with government, building trust and understanding in a complex integrated model. This is supported by a customisable modelling framework that is sufficiently flexible to adapt to changing policy needs in near real-time. We discuss how these attributes have facilitated cultural change within the Welsh Government where the IMP is being actively used to explore, test and iterate policy ideas prior to final policy design and implementation.

## Software and data availability

The ERAMMP Integrated Modelling Platform consists of a chain of models that are soft-coupled. Information on the availability of software for each model component is detailed below. Data availability for key datasets used by more than one model is detailed in Appendix A. Datasets used by individual models are included in the tables below.

| | |
|---|---|
| Name of software | Ecological Site Classification (ESC) |
| Developer and contact information | Stephen Bathgate and Duncan Ray, Forest Research (stephen.bathgate@forestresearch.gov.uk) |
| Year first available | The ESC decision support tool has been available since 2001, with the R script available since 2013 |
| Hardware required | Windows (16 GB RAM) |
| Software required | R |

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Available online 6 September 2023

(*continued*)

| | |
|---|---|
| Programming language | R |
| Program size | <2 MB for the script. 100 GB storage for input files |
| Software availability | An online version of the ESC Decision support tool for use at individual sites is available at: http://www.forestdss.org.uk/geoforestdss/ The R script contains licensed information and is not open access |
| Cost | NA |

| | |
|---|---|
| Name of software | CARBINE |
| Developer and contact information | Robert Matthews and Paul Henshall, Forest Research (paul.henshall@forestresearch.gov.uk) |
| Year first available | The CARBINE model was first developed in 1988, with continual and ongoing development |
| Hardware required | High performance PC with multiple (16) cores, 64 GB RAM 4*16 GB memory |
| Software required | LINUX/UNIX, Fortran compiler, Visual Studio2019 |
| Programming language | Fortran, C++ |
| Program size | 2 GB |
| Software availability | Contains licensed information and is not open access |
| Cost | NA |

| | |
|---|---|
| Name of software | SFARMOD |
| Developer and contact information | Eric Audsley and Daniel Sandars (daniel.sandars@cranfield.ac.uk) |
| Year first available | The Silsoe Whole Farm model (SFARMOD) was first developed in 1981, with continual and ongoing development |
| Hardware required | Windows PC works well with i7-6700 CPU and 16 GB physical memory |
| Software required | Runs on Windows 10 and some earlier versions and a 32bit Linear Programming solver we use XpressMP (legacy version) |
| Programming language | Visual Basic 6 |
| Program size | 5 MB |
| Software availability | Contains sensitive and licensed information and therefore not open access |
| Cost | NA |

| | |
|---|---|
| Name of software | SFARMOD – ERAMMP post processing |
| Developer and contact information | Daniel Sandars (daniel.sandars@cranfield.ac.uk) |
| Year first available | ERAMMP post processing was developed for this project from 2018 with continual and ongoing development |
| Hardware required | Windows PC – works well with i7-6700 CPU and 16 GB physical memory |
| Software required | Windows 10 |
| Programming language | Visual Basic.NET 2017 |
| Program size | 12 MB |
| Software availability | Contains sensitive and licensed information and therefore not open access |
| Cost | NA |

| | |
|---|---|
| Name of software | Land Allocation Module (LAM) |
| Developer and contact information | Michael Hollaway and Ian Holman (mhollaway@ceh.ac.uk) |
| Year first available | 2020 |
| Hardware required | PC with Intel Core i7 8th Generation (8 GB RAM) |
| Software required | R Programming Language (Version 4.2.1) |
| Programming language | R Programming Language (Version 4.2.1) |
| Program size | 1.6 MB |
| Software availability | The LAM code contains sensitive information and therefore is not open access. |
| Cost | NA |

| | |
|---|---|
| Name of software | Farmscoper |
| Developer and contact information | ADAS (richard.gooday@adas.co.uk) |
| Year first available | 2011 |
| Hardware required | Windows |
| Software required | MS Excel 2007 onwards |
| Programming language | MS Excel/VBA |
| Program size | 30 MB |
| Software availability | www.adas.co.uk/services/farmscoper/ |
| Cost | Free |

| | |
|---|---|
| Name of software | Ecosystem service models (LULUCF carbon, agricultural GHG & emissions from peatland, Water quality, Habitat connectivity) |
| Developer and contact information | Amy Thomas (athomas@ceh.ac.uk) |
| Year first available | 2019 |
| Hardware required | Windows (16 GB RAM, 25 GB storage) |
| Software required | R |
| Programming language | R (R 4.0.0 to 4.2.3) |
| Program size | <2 MB |
| Availability | Contains sensitive and licensed information and therefore not open access |
| Cost | NA |

(*continued on next column*)

(*continued*)

| | |
|---|---|
| Name of software | WRF 4.1.1 |
| Developer and contact information | National Center for Atmospheric Research (NCAR) https://doi.org/10.5065/D6MK6B4K Contact: user forum |
| Year first available | 2000 |
| Hardware required | High performance computer – multiple cores – usually we use ~128 cores |
| Software required | Linux/Unix, Fortran 95 compiler, NetCDF Library, MPI Library |
| Programming language | Fortran, Roff, C++, C, NASL, Shell |
| Program size | 1.2 GB (5 Gb – GFS-FNL data) |
| Software availability | https://github.com/wrf-model/WRF |
| Cost | NA |
| **Data & availability** (in addition to those listed in Appendix A) | |
| Source | GFS/FNL - National Centers for Environmental Prediction/National Weather Service/NOAA/U.S. Department of Commerce. (2000), updated daily. NCEP FNL Operational Model Global Tropospheric Analyses, continuing from July 1999. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory. https://doi.org/10.5065/D6M043C6. |
| Date/Version | ds082.0 |
| Link to access | https://rda.ucar.edu/datasets/ds082.0/ |

| | |
|---|---|
| Name of software | EMEP4UK rv4.34 |
| Developer and contact information | Norwegian Meteorological Institute (emep.mscw@met.no) |
| Year first available | 1970s |
| Hardware required | The EMEP code can run on a single CPU or in parallel with up to 1024 CPUs. If only one CPU is used 1–2 GB memory is required. If more than one, for example 64 CPUs are used, 200 MB of memory per CPU is enough (in the case of a 132 × 159 grid size). For runs on more than 32 CPUs, a fast interconnect is recommended (infiniband for example). |
| Software required | Linux/Unix, Fortran 95 compiler, NetCDF Library, MPI Library |
| Programming language | Fortran |
| Program size | 40 Mb (4 TB of WRF model input) |
| Software availability | https://github.com/metno/emep-ctm License: GPL-3.0 license |
| Cost | NA |

| | |
|---|---|
| Name of software | MultiMOVE |
| Developer and contact information | Simon M Smart (ssma@ceh.ac.uk) |
| Year first available | 2010 |
| Hardware required | PC and PC with multiple cores for parallel processing if required using library (futures) |
| Software required | R |
| Programming language | R |
| Program size | 206 Kb (R workflow), 58 Mb (MultiMOVE R package0 |
| Software availability | https://catalogue.ceh.ac.uk/documents/94ae1a5a-2a28-4315-8d4b-35ae964fc3b9 |
| Cost | Free |

| | |
|---|---|
| Name of software | BIMLA |
| Developer and contact information | Joseph Cooper and Gavin Siriwardena (joe.cooper@bto.org). |
| Year first available | 2023 |
| Hardware required | High-performance PC |
| Software required | R |
| Programming language | R |
| Program size | 184 kb (R workflow) c.840 MB (Input Datasets) |
| Software availability | By request from the BTO authors, noting that background data required to estimate predictions may require a licence for use |
| Cost | NA |

## 1. Introduction

Many real-world policy problems involve complex interrelationships across domains, sectors or disciplinary boundaries and, thus, need to be tackled using systemic approaches (Harrison et al., 2016; Holman et al., 2017; Huber et al., 2014; Laniak et al., 2013; Leclère et al., 2020). Agricultural and environmental policy is particularly multifaceted, covering, for example, policy areas related to climate change mitigation and adaptation, reversing declines in biodiversity, improving water quality, improving air quality, sustainable agricultural productivity, sustainable management of natural resources, conservation of heritage, and improving social outcomes (e.g. public access, outdoor recreation). Major shifts in any of these policy areas (e.g. agricultural support schemes) have the potential to cause unintended consequences on the desired outcomes from others (e.g. water quality deterioration resulting from incentivising agricultural intensification to enhance food security and economic performance) (Kopittke et al., 2019; Meyfroidt et al., 2018; Simoncini et al., 2019). Integrated modelling that allows the holistic assessment of alternative options or interventions has emerged as one approach for supporting complex policy or business decisions (Jones et al., 2023; Harrison et al., 2018; Kirchner et al., 2021; Riahi et al., 2017).

Integrated models have been developed and applied in a variety of policy-relevant contexts, as described in reviews by Laniak et al. (2013) and Kelly et al. (2013) for integrated environmental models (IEM), Weyant (2017) and Pauliuk et al. (2017) for cost-benefit integrated assessment models (IAM) of climate change mitigation, and Kirchner et al. (2021) and Hamilton et al. (2015) for integrated modelling in general. Such models operate at a range of spatial scales depending on the problem they aim to address. For example, relatively small-scale IEMs have been used to investigate sources of chemical pollutants in the Venice Lagoon (Sommerfreund et al., 2010) or determine appropriate responses to oncoming hurricanes, storm surges and flooding (Akbar et al., 2013). Conversely, IAMs are generally implemented at large scales, often globally, to assess the expected economic costs of climate mitigation policies and identify financially optimal solutions (IPCC, 2014; Fisher-Vanden and Weyant 2020). Importantly, many of these models are able to assess the relative influence of different management and policy interventions on environmental and economic outcomes. Therefore, integrated models have the potential to facilitate decision-making that accounts for trade-offs between distinct and diverse disciplines, and streamlines the movement of knowledge from researchers to end-users (Laniak et al., 2013).

The value of integrated modelling for providing evidence for emerging policy needs has been recognised by the UK government and its devolved administrations (Jones et al., 2023; Smith & Harrison et al., 2023; Thomas et al., 2021). The need for integrated evidence has also become more urgent following the UK's exit from the European Union, which has necessitated the design of many new domestic policies. This includes agricultural and environmental policies, which are devolved to the four nations of the UK (Wales, England, Scotland and Northern Ireland). In particular, the Welsh Government (WG) recognised that their pre-existing data and models were unable to provide the necessary systemic evidence-base to support the design of their new agricultural and environmental policies (James Skates pers. Comm. 2021). An integrated and long-term perspective to policy design is also required by WG to meet current legislation, particularly the Wellbeing of Future Generations (Wales) Act 2015 and Environment (Wales) Act 2016, both of which put an emphasis on addressing multiple outcomes in a holistic way.

However, only a few integrated models have been developed previously within the UK. These include the first regional integrated model (RegIS) that was developed to assess the integrated effects of climate and socio-economic change on agriculture, water resources, coastal and fluvial flooding, and biodiversity in two regions of England using linked meta-models (Holman et al., 2005, 2008). A similar approach was used by the CLIMSAVE/IMPRESSIONS Integrated Assessment Platform to explore the impacts of, and adaptation to, climate change on agriculture, forestry, water resources, biodiversity, urban development and coastal/fluvial flooding in Scotland (Holman et al., 2016). Finally, TIM (The Integrated Model – and its later web-based version NEVO) was developed as an integrated environment-economy model to assess the economic impacts of climate and land use change on a range of ecosystem services for the UK National Ecosystem Assessment (Bateman et al., 2014; Binner et al. n.d.).

Despite the potential benefits of integrated modelling for facilitating joined-up, rather than siloed, policy-making, they have rarely been used to design and evaluate policy within national governments. Integrated models are often developed by academics, but rarely subsequently used in anger as part of the policy cycle. This lack of uptake in decision support has been attributed to the opaqueness of integrated models (Robertson, 2021; Wilson et al., 2021), inadequate transparency in assumptions (Skea et al., 2021; Martinez-Moyano 2012), limited stakeholder engagement in the modelling process (Voinov et al., 2016), and lack of flexibility to address evolving policy needs (Argent 2004; Ewert et al., 2009). The existing integrated models for the UK suffer from many of these criticisms. In particular, their hard-wired, inflexible system architecture limits their ability to address rapidly evolving policy needs in near real-time.

WG, therefore, commissioned the co-creation of an integrated modelling platform (the ERAMMP[1] Integrated Modelling Platform or IMP) for Wales that could provide business-critical evidence to support the development of new policies focused on agriculture, land-use and natural resource management under a range of Welsh economic, regulatory and trade futures. The aim of the platform was to allow emerging policy ideas to be explored, stress-tested and iterated prior to final design and implementation.

This paper describes the IMP; one of the first integrated models to be classified as business-critical by a national government to the authors' knowledge, and an example of how integrated modelling can directly inform and benefit government decision-making over several years. The iterative co-creation approach used to develop and apply the IMP attempts to overcome criticisms of the utility of integrated models for decision support by building trust and understanding in the model and its outputs. The IMP advances existing integrated models by choosing a soft model-coupling approach that provides a customisable modelling framework that is sufficiently flexible to adapt to changing WG needs. This soft-coupling approach is key to the flexible integration, as 'people' (academics and WG working in partnership) are the enablers of fast model adjustment to evolving WG business-critical policy questions. This retains the active expertise in the model components within the IMP, rather than transferring the components to a central or external (to WG) modelling team. It also enables delivery at a pace that allows adaptation of WG policy thinking as model outputs emerge. This paper describes the overall iterative approach to the co-creation of the IMP and its modelling framework comprising eleven component models (covering agriculture, forestry, land use decisions, biodiversity and ecosystem services related to carbon, water quality and air quality). Evaluation of the model for current conditions and application of the model for four illustrative policy scenarios is then presented. Finally, lessons learnt for successful application of integrated modelling in decision support are discussed from the dual perspectives of the modelling and policy teams involved.

## 2. Methods

### 2.1. Iterative co-creation approach

The IMP was developed following the principles of co-creation,

[1] Environment and Rural affair Monitoring and Modelling Programme.

taking an iterative approach involving the modelling consortium and Government experts. The co-creation approach started with discussion of the type of policy questions to be asked and which models to incorporate. Together, these aspects shaped the requirements of the integrated model.

The development of policy questions was itself an iterative and emergent process, with questions being framed very broadly (often vaguely) initially and becoming more refined over time as understanding grew between the modelling team and Government experts of what it was possible to represent in the integrated model in relation to specific policy needs. This was summarised as a requirement to evaluate the impacts of different interventions aligned to WG policy objectives (such as payments to farmers associated with a new sustainable farming scheme) and external drivers (such as changes in commodity prices due to new trading relationships with the EU and other nations) on Welsh agricultural, socio-economic, and ecosystem service outcomes. However, it was recognised that the modelling framework would need to be adaptable in an iterative and agile manner as policy needs, and related questions, were likely to rapidly evolve based on internal Government discussions and external stakeholder consultations of draft policy designs.

Discussions on which models to incorporate in the integrated modelling framework involved the modelling team providing a transparent, honest and open understanding of the capabilities and limitations of available models to WG, including their suitability to the Welsh context and policy questions. The modelling team provided this information to WG for a wider list of available models than were ultimately chosen to include in the platform as part of the commissioning process for the IMP. Several criteria were used to select the most appropriate models to include: (i) well-tested in previous research and policy applications; (ii) appropriate for multi-scale spatially-explicit policy assessment studies; (iii) produced a wide range of policy-relevant outputs; (iv) responsive to a wide range of environmental, policy and market drivers; (v) use readily available public data as inputs; (vi) enable quantification of uncertainties for the estimations; (vii) suitable for integration, in that points of contact exist between the models; and (vii) easily adapted to ensure the modelling framework could be iteratively customised to changing WG needs. These discussions took place at the same time as refining the policy questions and led to agreement over the set of models and the best available and most recent datasets (Appendix A) to be included in the modelling platform. This information was used to co-create a detailed specification describing the individual system components, linkages (i.e. which outputs from which models will form inputs to other models), how they respond to different drivers (including policy drivers), and the spatial and temporal scale of simulation. In developing the specification, the modelling team identified where existing models may need to be modified or new models developed to either link component models or fill gaps.

An important part of the co-creation process was ensuring the IMP was 'fit-for-purpose', as WG designated the model as "business-critical" because it supports the development of core elements of government policy. "Business-critical" designation requires compliance with the UK Government's Aqua Book (HM Treasury 2015), which sets out stringent principles of "R.I.G.O.U.R." within which any analyses for government should take place: analysis should be **R**epeatable, **I**ndependent, **G**rounded in reality, **O**bjective, have **U**ncertainty managed and be **R**obust with respect to the initial question. This ensures analyses are conducted in a transparent manner with appropriate quality assurance of inputs, methodology and outputs in the context of the risks their use represents. The principles of RIGOUR were strictly adhered to with all assumptions underlying the modelling approach agreed, transparently documented and signed-off by a Senior Responsible Officer within WG following a multi-stage iterative discussion between modellers and end-users. In addition, modelling teams employed a range of appropriate methods for quality assurance, including validation, sensitivity analysis, contextualisation and interpretation, and detailing historical peer review, and produced a quality assurance document that detailed all these procedures for sign-off by the Senior Responsible Officer within WG.

The co-creation of the IMP has been a continually evolving process over the 6 years of the work to date based on two competitively commissioned tenders: ERAMMP for 5-years (November 2017 to October 2022 in two phases) followed by ERAMMP2 for 10-years (November 2022 to October 2032 in five phases). Over this period, the co-creation process was led by two people from the modelling team (the modelling lead and project manager) and two people from WG (head of the evidence team who commissioned the IMP and a liaison person to the relevant WG policy team for the model run(s)). Regular online 3-weekly meetings take place of this IMP management team, with others joining these meetings as needed. In addition, the full modelling team meet monthly to discuss the work needed and its timing to operationalise the agreements and actions from the management team meetings. Furthermore, ad-hoc meetings between representatives from WG and the modelling team are organised for specific needs, such as discussing and agreeing parameterisation of the IMP for each model run or co-development of a new component model specific to the Welsh context (the Land Allocation Module, see section 2.2.3).

The scoping and co-development of the IMP took place over the first 20 months of the project with a prototype of the IMP being demonstrated to the WG Strategic Evidence Group at an in-person meeting in July 2019. Following feedback, the IMP was further developed for another six months before moving into different phases of model application to support various policy processes from 2020 onwards, with 31 model applications being completed to September 2023.

To evaluate lessons learnt from the co-creation approach a questionnaire survey was sent to key WG individuals involved in the process in May 2021 and returned in July 2021 (see Appendix H). Seven WG officials responded to the questionnaire. Quotes from the responses from WG are included in the Discussion section where lessons learned from the perspective of both the academic team and the WG policy teams are discussed in more detail.

### 2.2. *Overall integrated model framework*

The IMP is a linked modelling system which includes 11 models representing different components across the agriculture, land-use and environment sectors (Fig. 1). Scenario settings developed in collaboration with WG are used to parameterise all models in the chain depending on the policy question being asked of the modelling system (Fig. 1, Box 1). The top half of the chain (Fig. 1, Boxes 2, 3 and 4) determines the impact of the scenario settings on agricultural and forest profitability at the farm scale, and thus on land-use allocation and management. The model is parameterised at a sub-farm level with biophysical constraints (e.g. climate, elevation and soils) and constraints based on environmental designations, and these are used to ascertain the most economically optimal configuration of each farm under a wide array of possible farm types. The Land Allocation Module (Fig. 1, Box 5) takes these farm types and decides which is most likely in the scenario after taking into consideration (i) the profitability of each farm type, (ii) the level of finance required for a farm to continue to function as a full-time farm, and (iii) the level of capital required to transition to a more profitable farm type. This new land allocation, along with the associated farm and forest data (number of sheep and cattle, area and species of trees etc.), is passed on to the models at the bottom of the chain (Fig. 1, Boxes 6–10) to ascertain the environmental impacts on greenhouse gas (GHG) emissions, carbon sequestration, air quality, water quality (including their monetary values) and biodiversity.

The IMP operates at various spatial scales depending on what is most appropriate to the indicator being modelling, for example, agricultural indicators are typically simulated at field or farm scale, whilst water quality indicators are accumulated across river catchments. Each simulated farm is modelled as a set of Decision-Making Units (DMU), which are fields or clusters of fields defined according to farm-specific

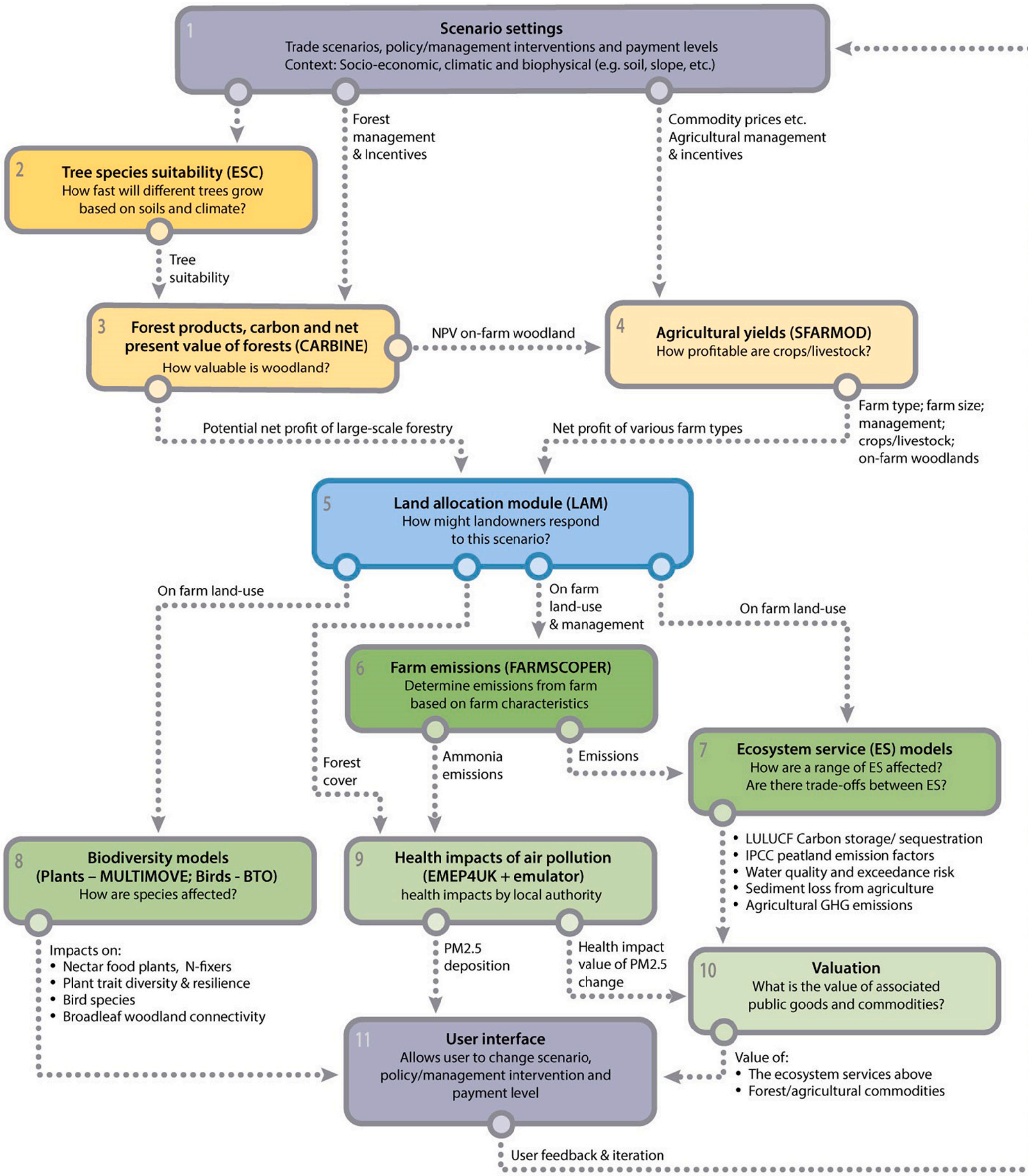


**Fig. 1.** Simplified schematic displaying the component models of the ERAMMP IMP and the links between them. Boxes represent either inputs, component models or the user interface. Arrows represent the flow of data, with text illustrating the types of data being passed between models.

discretised (banded) soil, rainfall, slope, altitude and recent farm type and land cover. It was agreed during the scoping phase with WG that farms with less than 1 full-time equivalent (FTE) of labour would be excluded from the agricultural modelling. The rationale was that smaller "micro farms" were likely to be farming for lifestyle reasons, with income being made elsewhere and, hence, it would not be appropriate to predict changes in their behaviour based on economic drivers.

The IMP is not a dynamic model. The requirement from WG was for the integrated model to broadly represent "short-term" and "long-term" consequences of their policy designs, and that it should not claim a false sense of precision given the wide array of factors that influence farmer and land manager decision-making, many of which cannot be modelled accurately (e.g. farmer behaviour, socio-cultural context, non-agricultural income). Hence, each model has its own temporal structure and time is only synchronized across the modelling chain to represent the "short-term" defined as the consequences of the policy design if farms remain in their current farm type and the "long-term" defined as consequences if farms can transition to more profitable farm types through conversion or sale and purchase.

The IMP uses a soft-coupling approach to model integration. This involves passing large "data cubes" between the modelling teams. Data cubes are multi-dimensional arrays of values that maintain a consistent internal structure between model runs, growing in size as more data become available. This approach has been essential to maintain flexibility and allow institutions to use their own proprietary software within a collaborative project. WG therefore has direct access to best-in-class models without the need to develop their own in-house modelling capability. The data cube approach also facilitates fast querying of model outputs and provides the potential benefit of plug-and-play, allowing models to be updated, added or swapped in and out with minimal disruption. The integrity of linkages between models is controlled by creating data dictionaries that detail the expected inputs and outputs provided by each model. These include the type, format and name of the variables passed, as well as the model the data came from and the model to which the data are passed. Data cubes were considered to be more flexible and scalable than alternatives, such as linked meta-models or emulators (e.g. Harrison et al., 2013), as they can grow over time as the modelling system adapts because they are n-dimensional.

Each component of the IMP is briefly described in the following sections.

#### 2.2.1. Forestry models (ESC and Carbine)

The Ecological Site Classification model (ESC; Pyatt et al., 2001) and CARBINE forest sector carbon accounting model (Matthews et al., 2022) collectively estimate the productivity and carbon storage potential of forestry. Timber prices and the costs of establishing and managing forestry is then used to estimate the profitability of different forest management options at the scale of a farm holding. These outputs are passed to the agricultural model (Section 2.2.2) to allow on-farm woodland to be considered as a potential land-use within a farm.

ESC is a decision support system for assessing tree species suitability and forest productivity (Yield Class, $m^3ha^{-1}yr^{-1}$) for a given site based on six climatic and soil variables. ESC has been used for national strategic and policy assessments for current and future tree species suitability and ecosystem service provision and is used widely across the forestry sector (Beauchamp et al., 2014; Ray et al., 2017). ESC was implemented as an R script at a 250 m resolution grid across Wales for eleven key tree species. The highest yielding species was selected to be indicative of each of three forest types: (i) productive conifers (Sitka spruce (*Picea sitchensis*), Douglas fir (*Pseudotsuga menziesii*), Scots pine (*Pinus sylvestris*)); (ii) native broadleaves (oak (*Quercus petraea, Quercus robur*), beech (*Fagus sylvatica*), aspen (*Populus tremula*), birch (*Betula pendula, Betula pubescens*); and (iii) short rotation forestry (Sitka spruce (*Picea sitchensis*), red alder (*Alnus rubra*), poplar (*Populus nigra*)). Five forest management types were simulated: (i) productive conifers (thin-fell), (ii) productive conifers (Low Impact Silvicultural Systems, LISS), (iii) native broadleaves (LISS), (iv) native broadleaves (no-thin--no-fell), and (v) Short Rotation Forestry (SRF) with a 25-year rotation. Data on tree species, forest management, yield class, climate zone, soil class, and previous land-use are passed from ESC to the CARBINE forest sector carbon accounting model.

CARBINE is a forest growth model, which has been applied in national GHG inventories under the United Nations Framework Convention on Climate Change (Brown et al., 2021a,b) and forms the basis of the UK's GHG emissions and removals due to afforestation, deforestation and forest management reporting under the Kyoto Protocol. The model calculates the development of carbon stocks over time in all key woodland carbon pools (trees, deadwood, litter, soil), wood production over time for key raw product types (sawlogs, small roundwood and bark), and GHG emissions from fuels, materials and machinery involved in creating and managing the woodlands. Estimates of carbon stock were made for each forest management type, for each 250 m grid location and for three time horizons (2020–2025, 2026–2050 and 2051–2100).

Forest profitability is calculated as annualised Net Present Value, including establishment and management costs, and profit from harvested wood products as determined by the CARBINE model, discounted over the rotation length using Green Book discount rates (HM Treasury 2022), with no grant payments included.

#### 2.2.2. Agricultural model (SFARMOD)

The Silsoe Whole Farm model (SFARMOD; Annetts and Audsley, 2002) estimates the profitability of various agricultural activities within each full-time farm holding in Wales using user-specified management and policy options. These options include agricultural subsidies and rules relating to the area of land under different management types (e.g. sheep, wheat, fallow, etc.), and options for on-farm woodland using data passed from the forestry models (Section 2.2.1). Given a particular scenario and set of management and policy options, SFARMOD estimates the profitability of both the current farm type and all potential alternative farm types for each farm holding.

SFARMOD is a constrained optimising strategic farm planning model based on profit maximisation, solved by Linear Programming. The model has been extensively applied across a range of farm types and scales (e.g. Hutchings et al., 2018; Holman et al., 2017). SFARMOD finds the optimum stocking, cropping, manure usage, fixed costs, labour and profit for given land quality, climate and a selection of available resources, constraints, costs and revenues. For the livestock farms that dominate in Wales, it provides an economic optimum farm management that ensures that the feed and bedding demand of the optimised livestock numbers through the year can be met by a farm-specific combination of on-farm feed production and bought-in concentrates. The nutritional demands of livestock are represented by fortnightly demands for metabolisable energy, crude protein and dry matter intake, along with bedding demands to meet welfare needs, which must be met within acceptable tolerances. Within their grazing seasons, suitable stock are all fed grazed grass (based on disaggregated yield using Qi et al. (2017)), with supplements, mainly for dairy cows. The model chooses the least cost ration (considering grass silage, a self-fed forage crop (roots), whole crop silage, maize silage, straw and concentrates), so that grass use is normally maximised. Due to data constraints, representative farm types (e.g. lowland dairy farms, sheep farms in severely disadvantaged areas) are used to define a set of realistic farming systems per DMU to solve with SFARMOD. Each DMU is optimised independently and then additively combined to obtain the solution for the farm.

#### 2.2.3. Land allocation model (LAM)

The current and future (scenario) profitability of each farm, based on the outputs from the agricultural model (Section 2.2.2) are compared within the Land Allocation Module (LAM) to simulate potential farming system change. To do this the LAM has been co-created with WG experts as a heuristic-based decision model containing co-developed and agreed rules and thresholds that reflect Welsh farming by selecting the expected long-term outcome for each farm (and their associated land-use and livestock selections) across Wales. Under a given scenario, the LAM considers multiple optimised SFARMOD farm solutions that include the holding's current farm type (e.g. dairy) and all alternative farm types (e.g. mixed livestock, specialist sheep etc.). The LAM estimates the Farm Business Income (FBI) for each farm based on the SFARMOD net farm profit, allowing for miscellaneous non-agricultural income, unpaid labour and the costs that do not change directly with farm plans (e.g. land ownership or tax) using farm type-specific data from the Welsh Farm Business Survey.

The LAM recognises that there are complex human and financial factors that affect the likelihood of a change in farm type in response to changing economic circumstances. These are reflected in the co-developed rules and FBI thresholds that represent "trigger events" (Sutherland et al., 2012; Padel et al., 2019) for initiating farm-level change, and which are used to identify farms under economic pressure, farms that remain in their current farm type, and farms that transition to more profitable alternative farm types. Farms under economic pressure fail to achieve a simulated FBI of less than £6000 p.a. (based on Hubbard 2019; Hubbard et al., 2018) and either leave full-time agriculture, are sold and converted to an alternative farm type or are afforested, depending on the viability and environmental suitability of alternative farm types and forestry (from the forestry models, Section 2.2.1). Farms remain in their current farm type if they exceed the minimum FBI threshold but either fail to achieve an FBI that provides the financial resources needed to change farming system or if there is no sufficiently financially attractive alternative to incentivise transition. Farms transition to a more profitable alternative farm type if the FBI uplift is sufficient to both incentivise change and to meet the cost of additional borrowing required to make the change (based on Welsh Farm Business Survey data and Andrew Moxley pers. comm.). Further information on the LAM is provided in Appendix B.

#### 2.2.4. Farm emissions model (FARMSCOPER)

Once the predicted land allocation is established for each farm using the LAM (Section 2.2.3), the agricultural emissions model, FARMSCOPER, determines the emissions from each modelled farm. FARMSCOPER (Gooday et al., 2014) is an export coefficient-based model derived from simulations of multiple different models of varying complexity. It calculates annual average losses to water of sediment, nitrate and phosphorus, and to air of ammonia, nitrous oxide and methane. The model uses cropping and livestock data for three representative farm systems (extensive and intensive grazed livestock systems and an arable system) derived from the June Agricultural Survey for Wales, alongside other information on farm management from national surveys for Wales and England (e.g. the Welsh Farm Practice Survey (Anthony et al., 2016) and Defra Farm Practice survey (FPS)). This farm management information includes, for example, the proportion of manure stored and spread directly and the uptake of various mitigation measures (e.g. the uptake of 'Manure Spreader Calibration' is based upon the results of the 2013 Defra FPS, which found that 58% of farmers never calibrated their manure spreader).

The three farm systems are modelled for each soil type and climate zone available in FARMSCOPER. The resultant source apportioned pollutant losses are then re-expressed as a function of the input data to provide pollutant loss coefficients per unit input that can be scaled against the appropriate unit outputs from the agricultural model SFARMOD (with each SFARMOD DMU assigned a FARMSCOPER soil type, climate zone and farm type). For example, the pollutant loss that FARMSCOPER attributes to dairy slurry is expressed per kg of N in dairy slurry so that it can then be scaled by the kg of N in dairy slurry simulated by SFARMOD. This coefficient approach allows the losses predicted by FARMSCOPER to scale with the input data from SFARMOD, which vary between DMUs and potentially change under different scenarios.

### 2.2.5. Ecosystem service models

A series of ecosystem service models use the information from the LAM (Section 2.2.3) on changes in on-farm land-use and management to estimate changes in carbon, water quality and air quality.

*2.2.5.1. Carbon models.* Carbon sequestration due to land-use, land-use change and forestry (LULUCF) and changes in peatland use are combined with the information from FARMSCOPER (Section 2.2.4) on GHG emissions from agriculture to estimate overall changes in carbon.

Carbon stocks in soils and biomass are calculated for agricultural land-use using LULUCF coefficients for Wales (Dyson et al., 2009; Annex 3 in Brown et al., 2018), and for woodland using CARBINE-ESC outputs (Section 2.2.1). For agricultural soils, the coefficients represent soil carbon in the top 1 m and are applied based on the combination of land-use and soil type (organic, organomineral, mineral, other). For agricultural biomass, the coefficients vary with land-use but not soil type. Rotational grassland/arable is assigned the same soil carbon stock as arable due to assumed frequent soil disturbance. Both carbon stock and change are calculated at the spatial resolution of the DMU taking into account that each DMU is a composite of different land-uses. Annual changes in carbon stock assume a non-linear rate of change and that some transitions occur more slowly than others. For example, for conversion of grassland to arable land, losses of carbon stock are initially high but then decrease exponentially over time. Changes in vegetation biomass projected by the LAM are assumed to occur straightaway (i.e. in year 1).

Carbon emissions from peatland are calculated using an approach aligned with planned future GHG inventory methods as per the IPCC wetland supplement (IPCC, 2014). Coefficients are derived from the draft wetland supplement (Evans et al., 2017) to align with LULUCF inventory methods and applied based on modelled land-use on peat. New woodland is not allowed to be planted on peat in the scenarios, and any peat portion of a field which is simulated to leave agriculture is assumed to revert to short vegetation.

Agricultural GHG emissions are calculated at the DMU level by combining each of the SFARMOD (Section 2.2.2) loading outputs (for fertiliser input, livestock excreta and land-use areas) with the relevant FARMSCOPER coefficient for methane and nitrous oxide emissions (Section 2.2.4), accounting for the climate zone, soil type and farm type. Changes are assumed to take place immediately.

*2.2.5.2. Water quality models.* Impacts on three aspects of water quality are simulated: (i) Water Framework Directive (WFD) phosphorus status; (ii) drinking water nitrate status; and (iii) sediment loss from agriculture. These are estimated from the farm emissions model (FARMSCOPER, Section 2.2.4) which uses the data passed from the agricultural model (SFARMOD, Section 2.2.2) on agricultural management for each DMU. Water quality impacts are assessed at the catchment scale by accumulating the loads calculated at the DMU level and converting to concentrations (as per Lee et al., 2015). This enables comparison with WFD target thresholds, which are concentration based.

SFARMOD only simulates farms with greater than 1 FTE labour, so FARMSCOPER was used to determine the pollutant loads for smaller farms using typical management data for such farms derived from farm surveys. Non-agricultural sources of pollutants are accounted for using outputs from the SEPARATE dataset (Zhang et al., 2014). Concentrations are calculated from the accumulated loads using regression relationships derived from the SEPARATE database and observed concentrations. Outputs for nitrate and phosphorus are processed to units reflecting the relevant thresholds: annual average concentration for phosphorus and 95th percentile for nitrate. Nitrate status is based on the EU Nitrate Directive target of 50 mg l-1. Sub-catchment-specific thresholds, provided by Natural Resources Wales based on altitude and alkalinity, are used to assign WFD status for phosphorus. The model simulates phosphorus concentration at the catchment outlet, so the most downstream threshold is used to assign status. Data on sediment losses are calculated as annual average loads rather than concentrations because highly event driven inputs and in-river processes occurring over a range of timescales can affect river sediment concentrations. Data outputs for all three aspects of water quality relate to a new long-term average reflecting land-use and management for the scenario; there is no accounting for time lags in the nitrogen system.

*2.2.5.3. Air quality models.* Changes in air quality as a result of land-use management and land-use change are calculated using the meta-model Meta-EMEP4UK, derived from the outputs of the atmospheric chemistry transport model EMEP4UK. The meta-model approach was adapted from Fletcher et al. (2021) and predicts the change in fine particulate matter ($PM_{2.5}$) concentration at a grid cell level (approx. 5 × 5 km). Inputs required for this calculation are the change in ammonia ($NH_3$) emissions (from FARMSCOPER, Section 2.2.4), current $PM_{2.5}$ levels, and the proportion of woodland within a 40 × 40 km grid (from the LAM, Section 2.2.3). Implications of these changes for human health, in terms of life years lost, are then computed.

In order to create the meta-model, two model runs were made using the atmospheric chemistry transport model EMEP4UK (Vieno et al., 2016): (i) a baseline run (BASELINE) with the current pattern of ammonia emissions, woodland and other land covers; and (ii) a bespoke land-use change and emissions change scenario (SCENARIO), which incorporated the full range of variation in ammonia emissions and woodland planting likely to occur under any of the land-use and management scenarios envisaged under policy change. This was achieved within a single spatial layer by variously increasing woodland proportion (current woodland cover, 50%, 100% cover), and ammonia emissions (current emissions, decrease by 75%, increase by +100%) in a randomly allocated pattern of 40 × 40 km grid cells. This scenario was constructed for the UK (rather than just Wales) to incorporate greater variation in background $PM_{2.5}$ concentrations, other atmospheric chemistry and meteorological variables, ammonia emissions and woodland area. Both model runs used 2015 emissions and meteorology.

The parameters for the meta-model were calculated by subtracting the SCENARIO from the BASELINE runs in EMEP4UK. The statistical meta-model calculates the change in $PM_{2.5}$ concentrations as a function of change in ammonia emissions, change in woodland cover and background $PM_{2.5}$ concentrations. The model structure was constrained by adjusting the intercept to ensure that modelled $PM_{2.5}$ concentrations did not change if there was no change in woodland and no change in ammonia concentrations. The resulting meta-model equation (adjusted $R^2 = 40.7\%$) is:

Change in $PM_{2.5}$ = [−0.20409]+(−0.18950*(Change in frac of woodland within 9 × 9 cell window *baseline $PM_{2.5}$)) + (0.000003*Change in $NH_3$ emissions).).

The change in $PM_{2.5}$ concentration is population-weighted to give an estimate of the change in exposure of the population. The change in exposure is converted to health impact metrics using response functions derived from COMEAP (2010) and Atkinson et al. (2014); compiled by independent experts for governmental use on the impact of $PM_{2.5}$ on respiratory hospital admissions, cardiovascular hospital admissions, Loss of Life Years, and the health costs associated with these. Health impacts are calculated as a proportional change in health outcome based on existing mortality and morbidity data by local authority, following approaches in Jones et al. (2019).

### 2.2.6. Biodiversity models

Species and habitat suitability for a wide range of plant and bird species is simulated using information on land-use and land management from the LAM (Section 2.2.3). Plants and birds were chosen to represent two contrasting trophic levels that are likely to represent potential change to wider ecosystems.

*2.2.6.1. Plant models (MULTIMOVE).* Changes in habitat suitability are estimated for 1188 plant species, including woodland and arable specialist plant species and positive Common Standards Monitoring (CSM) species (specialist plants of semi-natural habitats, e.g. lowland grassland, lowland wetlands, lowland heath and upland habitats) using MULTIMOVE. The model comprises an ensemble of Species Niche Models for British plants (see Smart et al., 2010, De Vries et al., 2010, Henrys et al., 2015; Smart et al., 2019 for full details of model building, testing and application). Five statistical modelling techniques (Neural Nets, Generalised Additive Models, Generalised Linear Models, Random Forest and Multiple Adaptive Regression Splines) are used to simulate the probability of occurrence of each plant species based on seven environmental variables measured or estimated at fine resolution in quadrat samples ranging from 4 to 200 $m^2$ in which full plant species lists were recorded. The species' input data for model building were presence/absence records. The output values from MULTIMOVE for each of the five statistical techniques is transformed into a single weighted model average based on a prior cross-validation test of the ability of each technique for each species to predict hold-out samples of the training data (Smart et al., 2019). A large GB-wide database of 32, 727 quadrats was used to build the models resulting in coverage of all habitat dominants and numerous rare and subordinate species.

The probability values that are output from MULTIMOVE are interpreted as habitat suitability indices because dispersal filters are not modelled (Smart et al., 2019). Therefore, an output value close to the maximum possible for the species (*pmax*) suggests that abiotic conditions are estimated to be appropriate for persistence should the species be able to reach the location and establish. To increase realism and constrain the species pool modelled in any one location, we restrict this pool to those species observed in each sample plot at baseline, plus the extra species recorded in the wider 10 × 10 km square based on data from the Botanical Society of Britain and Ireland (https://database.bsbi.org/). As MULTIMOVE models each species separately, results are aggregated across species to generate measures of functional group richness (Ferrier and Guisan 2006). The fine resolution, large geographical reach of the models and the number of species covered allow for very high local realism and very flexible model application at the field scale at which land-use decisions are made.

*2.2.6.2. Bird models (BIMLA).* Changes in bird populations resulting from shifts in land-use and management are estimated using a collection of statistical species-habitat predictive models (BIMLA - Birds in Modelled Land Assessment), developed from an established framework (e.g. Plummer et al., 2020). To derive bird counts, data were extracted from the BTO/JNCC/RSPB Breeding Bird Survey (BBS). This covered 315 spatially randomised 1 km squares across Wales during 2013–2017, from which count summaries (Plummer et al., 2020), were made for 68 species. Land-use metrics were then obtained for each 1 km square in Wales, representing different aspects of spatial coverage of land classes, characteristics and farming intensity (Appendix C). For all full-time farm holdings simulated by the IMP, these data are derived from 1 km square summaries of LAM outputs (Section 2.2.3). For land not covered by the IMP, these data were summarised from other landscape datasets (Appendix A).

To train the BIMLA models on species-land-use relationships, we extracted the land-use metrics for each BBS square, taking farm holding attributes as those of the baseline LAM output. A distinct model was developed per species through an iterative, generalised linear modelling procedure based upon Plummer et al. (2020). We assessed the relationship of each land-use metric with bird counts in turn, with all significant metrics ($p < 0.05$) included as predictors in a final species-habitat model. Once defined, we predicted counts for all 1 km squares in Wales using the R function, predict. glm. These were summed to provide an overall population estimate for each scenario with confidence intervals (Krinsky and Robb 1986). Thus, based upon localised changes in land-use and management, population-level changes could be assessed between different scenarios, including within individual species, species groups (as outlined by Bladwell et al., 2018), or within specific spatial regions.

*2.2.6.3. Woodland habitat connectivity model.* The effect of new on-farm woodland and afforestation (from the LAM, Section 2.2.3) on the connectivity between existing patches of broadleaf woodland is estimated based on overlap of areas within a dispersal distance of existing woodland. Habitat area requirements and dispersal distances vary between species types; hence, these overlapping areas are identified using a range of combinations for these parameters (see Appendix D). If new woodland falls within an overlap area, it is assumed to create new connectivity for the relevant species types.

### 2.2.7. Valuation of ecosystem services

In the final stage of the IMP integrated chain, the ecosystem services of carbon (climate regulation), water quality and air quality are valued in monetary terms to capture the change in welfare to wider society. Valuation follows a hierarchy of methods (market prices, avoided costs, revealed preference and stated preference) using value transfer approaches and following best-practice guidelines (e.g. ENCA 2021). Values are calculated for three time periods: 5, 25 and 75 years into the future, and converted to current prices using HM Treasury GDP deflators at market prices.[2] To give context to the monetary values, they are presented alongside physical values for all indicators, including biodiversity, and effects on farm business income. Each uses evidence derived from a different valuation method.

- Carbon: value per tonne of $CO_2$e according to the UK Department of Business, Energy and Industrial Strategy (BEIS 2019), which reflects the costs of having to meet climate change targets;

[2] https://www.gov.uk/government/collections/gdp-deflators-at-market-prices-and-money-gdp.

- Air quality: values based on the avoided costs of health impacts associated with air pollution, as a result of lower emissions from farming and woodlands removing air pollutants from the atmosphere (see Section 2.2.5.3); and
- Water quality: based on society's benefits from having a cleaner freshwater environment, using values derived from a stated preference study (Metcalfe 2012, based on NERA Economic Consulting, 2007).

### 2.2.8. IMP interface

The IMP interface is still under development as WG prefer rapid production of slidepacks showing key results with expert interpretation for exploring draft policy designs. However, the interface is expected to be utilised as policy designs stabilise and their communication to a wider audience is needed. The interface aims to provide interactive exploration and visualisation of the outputs from the integrated model. An agile development methodology ensures the interface adapts quickly to WG's requirements. Fast translation of model outputs to interface-ready inputs allow it to keep pace with the on-going modelling and remain policy relevant. Impacts of policy, as modelled through scenarios, can be explored nationally and regionally via charts, synchronized interactive comparison maps and tables. The user has control over colours and thresholds of equal interval classifications. To ensure clear and accurate communication of results, detailed metadata for each environmental indicator is integrated into the interface's dictionaries. Additionally, persistent URLs allow the user to easily share any view of the data they have created to facilitate collaboration and reporting. Further information on the technical implementation of the interface is provided in Appendix E.

## 3. Results

### 3.1. Baseline evaluation and quality assurance (QA)

The complexity of the modelling chain and the range of component models means there is no single activity for baseline evaluation and QA. Instead, a range of activities are undertaken, with each adding to the overall level of QA. These approaches include.

- ***Peer Review:*** Academic peer review of models is an important step in the assessment of a model's fitness-for-purpose. Most models within the IMP chain have a significant history of application within academic literature for addressing similar questions to those they are being used for by the WG. Others follow agreed standard approaches used for government reporting (e.g. the carbon model follows LULUCF carbon accounting procedures; and the valuation of ecosystem services follows Treasury Green Book guidance on appraisal and evaluation, HM Treasury, 2022). In other cases, (e.g. the water quality model) the coefficients are derived from a peer-reviewed model (FARMSCOPER) and combined with the outputs of another peer-reviewed model (SFARMOD); the combined outputs are then independently evaluated.
- **Version control:** Utilising a soft model-coupling approach requires strict QA and data management to ensure correct application and consistency across the IMP. Each data pass in the IMP is representative of a real-world interdependency and as such, any iteration in the 'upstream' models must be cascaded correctly through the chain. This is facilitated by the generation of ERAMMP Unique Identifiers (EUIDs). An EUID is assigned to each model, and each input and output dataset which facilitates traceable data flows to ensure version control, verification and repeatability.
- **Verification:** Verification is undertaken for all models and data passes to ensure models are functioning as expected and datacubes are error free. Verification processes and checks are tailored to each model, but include checking code for errors, setting checks to catch common errors in code or modelling teams using their own expert judgement to assess their model's performance is within expected parameters.
- **Documentation of assumptions:** For transparency and to build understanding with the WG, key parameters and all assumptions are documented, reviewed, tested, and signed-off by a WG Senior Responsible Officer. The final documented assumptions reflect a considerable period of iteration between the consortium modelling team and a range of experts within WG. This process increases the robustness of analysis by presenting the results in the context of residual uncertainty and limitations to ensure it is used appropriately.
- **Sensitivity Testing:** This was undertaken for models that were specifically developed for use in the IMP and, hence, do not have previous sensitivity testing reported in the peer review literature (e.g. the LAM).
- **Validation:** Due to the complexity of the modelling chain, the IMP was validated by assessing the results of each model element. All models were validated where possible, although the specific approach taken varies depending on the model and the available data. Full model validation was not always possible, either due to the methods employed or lack of available data. In these cases, thorough sense checks were undertaken.
- **Expert Assessment:** To support model validation, expert knowledge within the consortium and externally (including a WG expert group) is used to assess the data, assumptions, methodology and outputs. This process provides a (partly) independent check on model verification, validation, and any implications for the linked models. Whilst there are limits to constraining bias, the documentation of assumptions and expert assessment aims to identify and address any biases that are raised. This also provides opportunities for challenge by the end-user and increases the robustness of analysis and subsequent decision-making.

Table 1 shows which of the QA activities have been undertaken by which models in the IMP chain. All models have undertaken version control, verification, documentation of assumptions, validation and expert assessment, whilst peer review and sensitivity testing has been applied to some models where relevant.

While it is recognised that the sensitivity of the model components may be different to the sensitivity of the IMP itself, it was not possible to undertake a systematic sensitivity or uncertainty analysis across the modelling chain due to the time critical nature of the model results for supporting fast moving policy and the long runtimes of the sequence of models. Nevertheless, expert assessment by the modelling team and WG experts was used to ensure that there was no unacceptable propagation and magnification of uncertainty along the modelling chain. The documentation of assumptions and QA across the full integrated model following Aqua book guidelines also provided transparency about the limitations of the model. Full details of the baseline evaluation and QA of all models is documented in Harrison et al. (2022a) and summarised in Appendix F.

### 3.2. Illustrative scenario application

The IMP has been used extensively with the WG to explore the effects of different scenarios on agriculture, land-use, biodiversity and ecosystem services in Wales, but many of these applications remain confidential as they are used to test policy design. To illustrate the capability of the model, we describe results from one of a set of scenarios that are publicly available and consider the possible impacts of a free-trade agreement (FTA) with the EU, USA, Australia and New Zealand. The scenarios consist of changes in input costs and output prices (key output prices in Table 2), which were based on discussions held between

**Table 1**
QA activities undertaken by the component models in the IMP.

| Model | Version Control | Verification | Assumption Documentation | Expert Assessment | Validation | Sensitivity Testing | Peer Review (PR) and Standard Approaches (SA)[a] |
|---|---|---|---|---|---|---|---|
| SFARMOD agricultural model | ✓ | ✓ | ✓ | ✓ | ✓ | × | PR |
| ESC-CARBINE-NPV forestry models | ✓ | ✓ | ✓ | ✓ | ✓ | × | PR |
| Land Allocation Module (LAM) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × |
| FARMSCOPER emissions model | ✓ | ✓ | ✓ | ✓ | ✓ | × | PR |
| BIMLA bird models | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | PR |
| MULTIMOVE plant model | ✓ | ✓ | ✓ | ✓ | ✓ | × | PR |
| Habitat Connectivity | ✓ | ✓ | ✓ | ✓ | × | × | × |
| Water Quality | ✓ | ✓ | ✓ | ✓ | ✓ | × | Partial |
| Air Quality | ✓ | ✓ | ✓ | ✓ | ✓ | × | PR |
| Carbon | ✓ | ✓ | ✓ | ✓ | ✓ | × | SA |
| Valuation | ✓ | ✓ | ✓ | ✓ | ✓ | × | SA |

[a] Standard Approaches are those used for government reporting.

**Table 2**
Overview of the scenarios: brief description and key farm-gate output prices for baseline (2015) and each scenario.

| Scenario | Description | Farm-gate price | | |
|---|---|---|---|---|
| | | Milk (p/litre) | Beef (£/kg LWT) | Lamb (£/kg LWT) |
| Baseline | 2015 | 35 | 1.85 | 1.68 |
| EU | FTA with EU only | ↑35.4 | ↓1.80 | ↓1.66 |
| EAN | FTA with EU, Australia and New Zealand | ↑36.8 | ↓1.57 | ↓1.51 |
| ALL1[a] | FTA with all | ↑36.8 | ↓1.48 | ↓1.43 |
| ALL2[a] | FTA with all | ↓33.3 | ↓1.48 | ↓1.43 |

[a] Two versions of the FTA with all scenario were created to assess uncertainties over whether milk prices might increase or decrease.

stakeholders in the Evidence and Scenario sub-group (Roundtable Wales and Brexit[3]) and WG policy officials that took place in late 2020 before the arrangements for the UK leaving the EU were agreed. Further information on the scenarios is given in Harrison et al. (2022b).

The small changes in prices in the EU scenario lead to a small change in the number of farms under pressure, but also provide potential opportunities for farms to change to more profitable farm types (Fig. 2). In contrast, all other scenarios are very challenging for the current full-time farms in Wales due to the large reductions in lamb and beef prices, leading to a significant proportion of farms coming under pressure in all farm types, except dairying. Within ALL1 and ALL2, there are only a few farms that can change to more profitable farm types through deliberate action rather than through sale and purchase. This leads to significant numbers of farms being simulated to leave full-time agriculture; 22% in ALL1 and 29% in ALL2.

Under all scenarios, aggregate FBI is simulated to decrease for the current full-time farms without farm type transitions (Fig. 3). In all cases, simulated transition of farms (through either deliberate action or sale and purchase) either leads to smaller reductions in aggregate FBI (e.g. in ALL2 where prices decrease in all sectors, but by a smaller amount in the dairy sector) or can lead to an increase in simulated aggregate FBI for the remaining full-time farms (e.g. in EU, ALL1 and EAN due to increased milk prices).

An intensification of managed grassland systems is simulated on those farms remaining in full-time agriculture under all scenarios across Wales, with a 66–177% increase in temporary grassland and a 21–70% decrease in permanent grassland. This is associated with the large increases in dairy livestock numbers (+73 to +181%) and decreases in sheep numbers (−34 to −64%). Farms leaving full-time farming release agricultural land that is converted to woodlands through afforestation, or to woodland or short vegetation through natural regeneration of the land (Fig. 4). The smallest area of new woodland occurs under the EU scenario (6060 ha) and the largest under ALL2 (149,075 ha). New woodlands are mostly located in the upland and hill areas, which are dominated by the beef and sheep farms that are adversely affected by the larger price reductions compared to the dairy farms. Given the environmental conditions (e.g. soil, land cover, slope, climate), there are fewer alternative farm types that can achieve sufficient simulated FBI in these areas.

The changes in farm types and associated land-use result in mixed simulated impacts on biodiversity. For birds, 19–24% of populations are simulated to decline, whilst 17–59% improve across the scenarios. The majority of populations that are predicted to significantly increase are those that specialise in woodland habitats, with ALL1 and ALL2 being the most favourable scenarios (Fig. 5a). For plants, habitat suitability is predicted to decrease for 25–32% of species and increase for 3–15%. Improvements in suitable niche space for plant species are simulated across woodland, semi-natural and arable habitats, with much greater increases occurring in EAN, ALL1 and ALL2 compared to EU (Fig. 5b). In addition, almost all new woodland is simulated to create an increase in woodland habitat connectivity. This is greatest under the ALL2 scenario, which simulates the greatest increase in new woodland.

A net increase in atmospheric GHGs is simulated by 2100 under all scenarios (Table 3). Differences between the scenarios reflect the relative areas undergoing agricultural intensification or woodland creation, and the varying rates of carbon stock change over time under these transitions. All scenarios show initial losses for LULUCF carbon, reflecting intensification on some agricultural land, with some contribution from initial losses for new woodland. By 2050, the negative numbers for ALL2 indicate that sequestration for new woodland and other land coming out of agriculture offsets LULUCF losses on agricultural land undergoing intensification, and by 2100, significant sequestration is modelled. All scenarios simulate a reduction in peatland GHG emissions, which are greatest in the ALL2 scenario, due to agricultural land on peat soils coming out of agricultural use. However, the contribution to the overall change in atmospheric GHGs is relatively small in all cases. In all scenarios, except ALL2, the overall carbon budget is dominated by the modelled increases in GHG emissions associated with changes in livestock (increases in dairy cattle and decreases in sheep) and nutrient inputs, which greatly exceeds the predicted emissions from vegetation and soils associated with agricultural land-use change and

[3] https://gov.wales/evidence-and-scenario-sub-group-roundtable-wales-and-brexit.

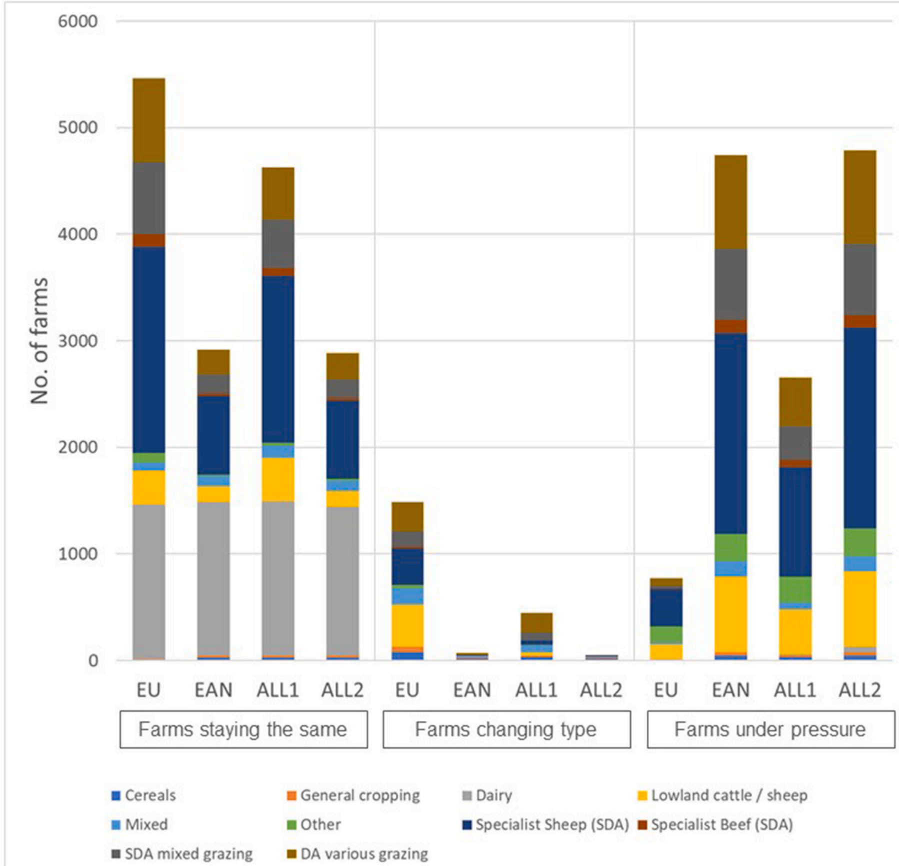


**Fig. 2.** Change in the simulated status of current farms for the four scenarios.

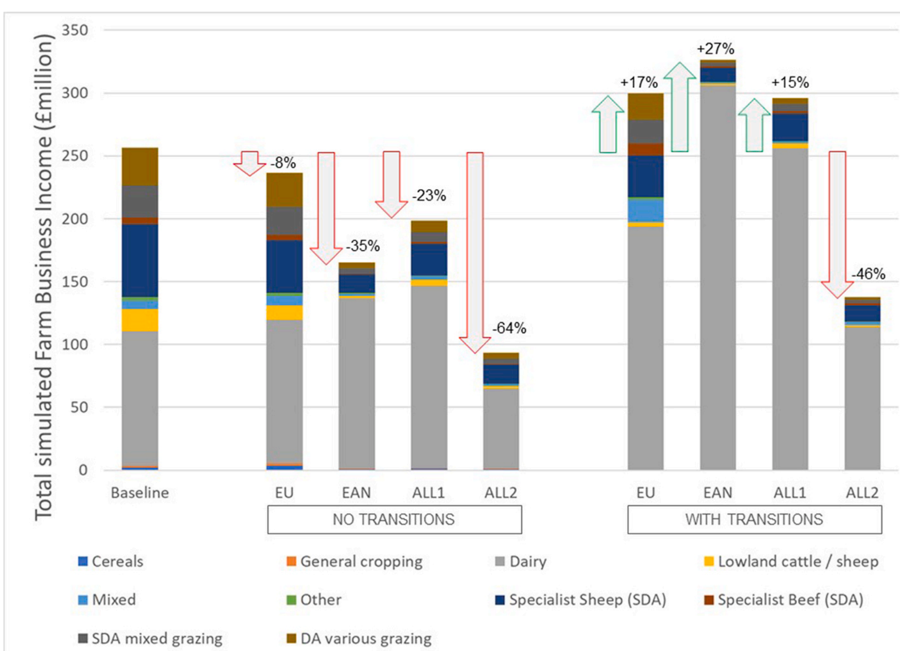


**Fig. 3.** Total simulated Farm Business Income from full-time farms under the four scenarios.

the carbon sequestration due to woodland creation.

Water quality indicators (nitrate, phosphorus and sediment) are projected to worsen under all scenarios, but ALL2, where phosphorus concentrations and sediment loads are simulated to decrease. The greatest proportional increase in pollutants is always modelled from nitrate, then phosphorus and then sediment. The spatial pattern of change in pollutant concentrations (e.g. Fig. 6 for nitrate concentration) reflects the relative contributions of different agricultural land-uses to

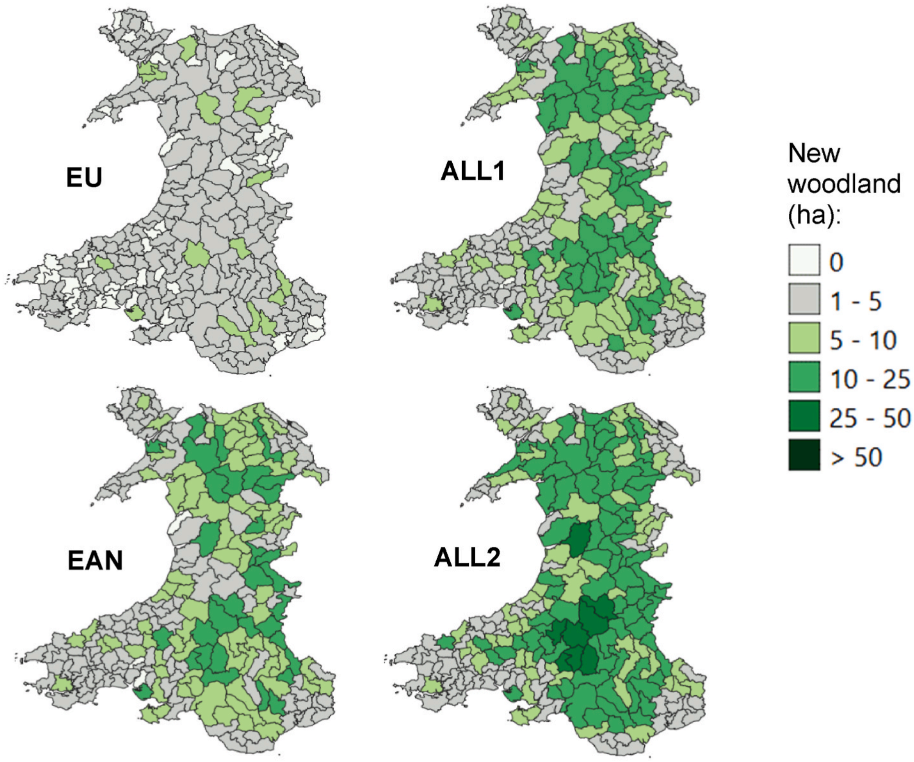


**Fig. 4.** Spatial distribution of new woodland establishment through natural regeneration and afforestation on farms that are expected to go out of agriculture (as hectares of new woodland per Small Agricultural Area) under the scenarios.

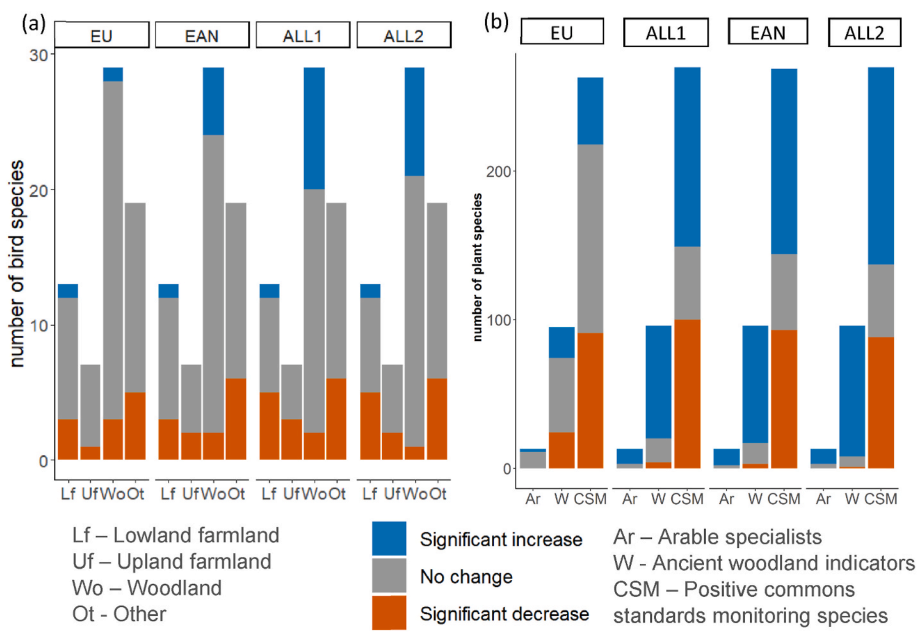


**Fig. 5.** Change in (a) bird populations and (b) habitat suitability for plant species associated with different habitats under the four scenarios. For (a), the significance of population changes was based upon 95% confidence intervals derived from the variance-covariance matrix of the species model parameters. Significant changes were reported where confidence intervals did not overlap between baseline & scenario. For (b), significance of changes in modelled habitat suitability for plants was based on a whether the 95% confidence interval of bootstrapped differences in suitability for each species included zero. Note, positive Common Standards Monitoring species are specialist plants of semi-natural habitats.

these different pollutant types and the pattern of agricultural change. The ALL1 scenario shows the greatest increases in nitrate concentration as dairy farms create more nitrate pollution when compared to other land-uses, whilst the ALL2 scenario shows decreases in nitrate concentration in the upland and hill areas of Wales where farms are simulated to leave full-time agriculture.

Air quality is simulated to deteriorate in the EU, EAN and ALL1 scenarios, reflecting the negative impacts of agricultural intensification and associated ammonia emissions outweighing the positive impacts of new woodland creation. Conversely, improvements in air quality are projected in the ALL2 scenario due to the greater area of farmland converting to woodland, particularly closer to urban settlements in Northeast, South and Southeast Wales.

Table 4 summarises the physical values for air quality, water quality and atmospheric GHGs alongside their monetary values. For each public good (row) the data reflects the aggregated changes over 75 years. Monetary values are negative for all three public goods under the EU, EAN and ALL1 scenarios, but positive for air and water quality under the

**Table 3**
Changes in GHG fluxes from LULUCF (4 A, B, C & G), peatland and agriculture (livestock and crops) (in $KtCO_2eq$) from baseline (2015) by three time periods (2025, 2050 and 2100).

| Scenario | 2025 | 2050 | 2100 |
|---|---|---|---|
| ***EU:*** | | | |
| LULUCF | 2960 | 8269 | 9668 |
| Peatland | −6 | −34 | −91 |
| Agriculture | 7101 | 42,606 | 113,617 |
| TOTAL | 10,055 | 50,841 | 123,194 |
| ***EAN:*** | | | |
| LULUCF | 5039 | 3756 | −199 |
| Peatland | −32 | −194 | −518 |
| Agriculture | 7735 | 46,412 | 123,765 |
| TOTAL | 12,742 | 49,974 | 123,048 |
| ***ALL1:*** | | | |
| LULUCF | 8644 | 12,330 | 8795 |
| Peatland | −47 | −282 | −753 |
| Agriculture | 13,912 | 83,470 | 222,586 |
| TOTAL | 22,509 | 95,518 | 230,628 |
| ***ALL2:*** | | | |
| LULUCF | 6007 | −29,849 | −55,133 |
| Peatland | −288 | −1366 | −3642 |
| Agriculture | 4195 | 25,172 | 67,125 |
| TOTAL | 9914 | −6043 | 8350 |

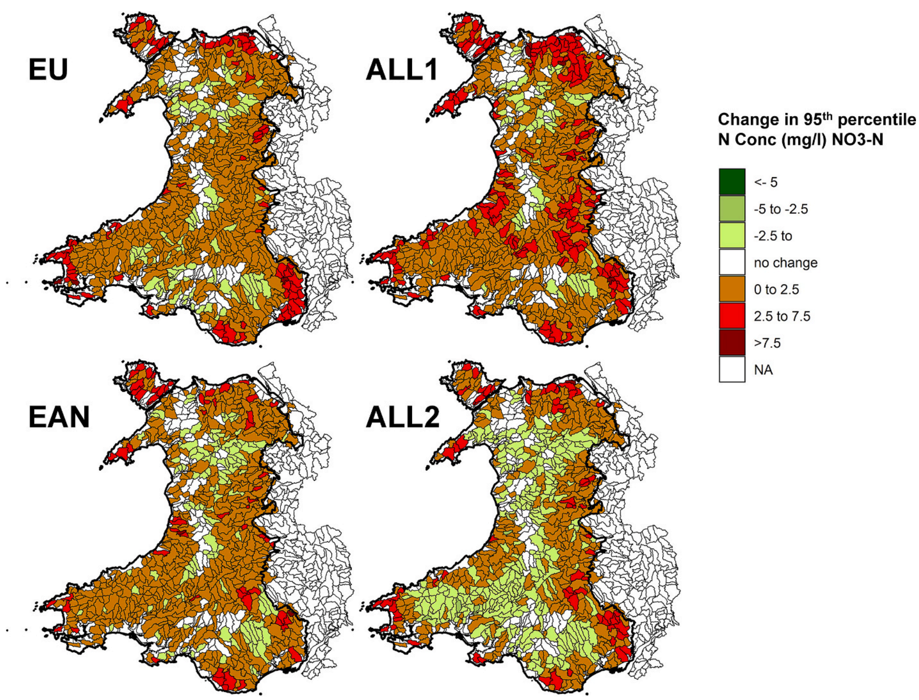


**Fig. 6.** Change in nitrate concentration for water bodies in Wales under the four scenarios.

ALL2 scenario. Public good values are dominated by the GHG values in all scenarios.

## 4. Discussion

In this paper we describe the co-creation of an integrated modelling platform that has been classified as "business-critical" by government. The ERAMMP IMP has been designed as a customisable modelling framework that provides the benefits of an integrated modelling approach but is sufficiently flexible to adapt to changing government needs in near real-time. The model is being actively used by the Welsh Government to explore, test and iterate business-critical policy ideas prior to final policy design and implementation. In particular, it is currently being used to support the design of a new Sustainable Farming Scheme[4] that is due to commence in 2025, which will be the main source of future Government support for farmers in Wales. As the results from these applications of the model remain confidential, we illustrate the capability of the model using four trade scenarios that have been approved as publicly available information.

The trade scenarios were designed to support the formation of an evolving agri-trade policy for Wales that builds positive response mechanisms for the agricultural sector and protects the environmental sector from negative impacts. Our results show that the least change in agriculture is simulated under the EU trade deal scenario, with 10% of

[4] https://www.gov.wales/sustainable-farming-scheme-guide.

**Table 4**

**Summary of public good values for the four scenarios based on a 75-year time horizon and 2020 prices. Colour of cell reflects cost (orange) or benefit (blue) in terms of total monetary value.** Air quality measured in terms of Life Years Lost each year; Water quality measured in terms of the number of water bodies with changes in WFD status due to changes in P and N; Greenhouse gases measured in terms of net change in atmospheric $TCO_2eq$ over 75 years.

| Scenario -> | EU | | EAN | | ALL1 | | ALL2 | |
|---|---|---|---|---|---|---|---|---|
| Value type -> | Physical | Monetary | Physical | Monetary | Physical | Monetary | Physical | Monetary |
| Air quality | +60 | - £85m | +29 | - £42m | +59 | - £85m | -54 | + £67m |
| Water quality | 65 dec<br>3 inc | - £33m | 59 dec<br>12 inc | - £26m | 108 dec<br>5 inc | - £47m | 58 dec<br>44 inc | + £4m |
| Greenhouse gases | +116m | - £8,037m | +116m | - £8,009m | + 218m | - £15,047m | + 7m | - £364m |

farms coming under economic pressure. The other scenarios simulate relatively large impacts on agriculture, with 34–62% of full-time farms coming under pressure and either leaving the agricultural sector or transitioning from farm types associated with sheep and beef systems to dairying. Hubbard et al. (2018) and van Berkum et al. (2016) found similar decreases in farm incomes in the UK under various Brexit scenarios, with more modest impacts under an EU free trade agreement, and cattle and sheep farm businesses being particularly challenged. Our simulated reductions in agricultural area led to increases in woodland area of 5% under the EU scenario and 32–116% for the other scenarios. These levels and spatial patterns of change are similar to findings by Thomas et al. (2021) and Manzoor et al. (2021) who project substantial increases in Welsh woodland under trade liberalisation scenarios, but smaller increases under an EU deal. Finally, we simulate increasing GHG emissions in all scenarios, declining air and water quality in three scenarios, and mixed effects on biodiversity. Thomas et al. (2021) also found mixed responses of bird abundance to different Brexit scenarios, which were dependent on the habitat requirements for each species. However, Thomas et al. (2021) projected reductions in GHG emissions under all their scenarios as their modelling only reflected woodland GHG mitigation. Since completing this modelling for WG, an EU trade deal has been agreed. Consequently, the EU scenario was used by the WG as the counterfactual scenario against which the costs and benefits of the land use implications of the proposed Sustainable Farming Scheme were assessed in the Regulatory Impact Assessment for the Agricultural (Wales) Bill 2022.

Notwithstanding the coherency between these results from the IMP and other peer-reviewed studies, there remain wider concerns as to the utility of integrated assessment models in informing policy in a range of contexts including climate mitigation (e.g. Gambhir et al., 2019; Skea et al., 2021), energy policy (e.g. Pfenninger 2017) and agricultural policy (e.g. Ewert et al., 2009). These criticisms include limited stakeholder engagement in the modelling process (Voinov et al., 2016), the opaqueness of the models (Robertson, 2021; Wilson et al., 2021), inadequate transparency in assumptions (Skea et al., 2021; Martinez-Moyano 2012), inadequate peer review (Rosen 2015), lack of flexibility to address evolving policy needs (Argent 2004; Ewert et al., 2009) and lack of communication of uncertainty (van Asselt and Rotmans, 2002; Wilson et al., 2021; Skea et al., 2021; Kirchner et al., 2021) that together lead to a lack of trust in model outputs. To help address these issues, Saltelli et al. (2020) proposed five principles for responsible modelling that recognise that "good modelling cannot be done by modellers alone".

We discusss the development, application and reporting of the IMP against these criticisms and summarise the lessons learnt that can inform the successful application of integrated modelling for decision support in other case studies. Lessons learnt focus on the importance of.

- **Iterative co-creation** through a long-term partnership between government and the modelling team to build **trust** and understanding in the integrated model and its outputs;
- **Transparency** of the model and its assumptions, including following government approved QA processes for the use of models in policy decisions;
- **Flexibility** of the modelling approach so that it can be rapidly adapted to changing policy needs, enabling **timeliness** of model runs that are delivered at a pace that is able to inform quickly evolving policy needs.

### *4.1. Iterative co-creation of trusted integrated models*

Co-creation has been a core part of the IMP development through a long-term, iterative, two-way and continuously evolving process with WG. Co-design and co-creation are important processes for developing two-way learning between those developing the models and those using the models in a way that builds trust (Voinov et al., 2016; Frame et al., 2018), allows end users to develop their understanding of a model (Rounsevell and Metzger 2010; IPBES, 2016; Iwanaga et al., 2018), and enables modellers to build in knowledge of the system studied from those whose questions they are answering (Voinov and Bousquet 2010; Landström et al., 2011; Ferrier et al., 2016; Iwanaga et al., 2018). Co-creation is an iterative and challenging reflexive process (Rounsevell and Metzger 2010; Voinov et al., 2016; Frame et al., 2018), especially in the context of integrated models which are often seen as complex, "black-box" systems with compound uncertainties (Gambhir et al., 2019; Robertson 2021).

The IMP modelling is business-critical to the WG, directly influencing decisions in active policy areas. As such it is imperative that WG understands and trusts the model outputs and is confident in their awareness of the questions that the modelling system can and cannot address (Rosen 2015; Voinov et al., 2016). WG end-users and the IMP team were both actively involved in the problem framing, the development of assumptions and the interpretation and critique of the results. The long-term partnership between WG and the IMP team with very frequent dialogue (weekly to monthly) means that both parties are learning throughout the process, improving stakeholder buy-in whilst ensuring that modellers understand the requirements of policy-makers (Lynam et al., 2007; Voinov et al., 2016; Iwanaga et al., 2018). It also exposes the model outputs to continual end-user and modeller critique so that the take home messages are understood in the context of the decisions made within the co-creation process (Voinov et al., 2016; Skea et al., 2021).

In responses to the survey to capture feedback from the WG on the IMP, co-creation was described as an "*essential*" element of the IMP approach. This furthered the WG's understanding of all steps of the modelling chain, a key benefit of co-designed frameworks (Rounsevell and Metzger 2010; Frame et al., 2018). For example, as a result of their involvement in the parameterisation of models, WG identified new datasets and improved their understanding of the limits of existing data. The process also led to improved policy thinking. For example, the co-creation of scenarios led to "*better understanding of the key drivers, on which to focus policy interventions*". Most importantly, the partnership working helped WG "*understand what the inputs and outputs are actually demonstrating*" which meant that they were better placed to "*interpret and present these findings to Ministers or stakeholders*". The iterative building of trust and understanding through co-creation has ultimately encouraged WG policy-makers to "*ask a question*" and not "*ask for an answer*" as they now realise that the IMP is an exploratory tool: "*a test bed*" that "*will give [helpful] answers only if you ask it the right questions*".

Finally, it is also important to recognise that the process of building trust is often facilitated (or hindered) by the individuals involved (Voinov et al., 2016). Trusted intermediaries or gatekeepers can play a vital role in building up two-way communications in a sensitive manner (Voinov et al., 2016). This was the case for the IMP where the WG lead was instrumental in influencing the buy-in and uptake of the modelling across policy departments within WG. The vision and willingness of WG in funding longer-term modelling and monitoring programmes (5–10 years in duration) also considerably supports the co-creation processes that are important for building trust and understanding in complex integrated models.

### 4.2. Transparency of assumptions in integrated models

Transparency and the use of plain language in documenting model processes and assumptions, which are often considered opaque and uninterpretable, helps users understand the uncertainties and limitations associated with the results (Voinov and Bousquet 2010; Rosen, 2015; Robertson 2021), ultimately leading to greater trust in the outputs (Pfenninger 2017; Skea et al., 2021). For the IMP, all assumptions were discussed transparently with WG, often leading to further questions, requests for clarification and supplementary analysis to build further understanding before they were signed-off by senior WG officials. For example, WG experts are aware that farmer preferences and attitudes are not included in the IMP, and hence farmers may not behave as simulated by the model. This transparency has made WG more confident that they understand the "*limitations of the IMP outputs, and the assumptions on which they are based*". This "*created growing knowledge in WG that the outputs of the IMP are not the gospel truth and instead are estimates*" and ensured that the outputs are "*used appropriately with other evidence sources, but which also maximises their usefulness to policy development*". Transparency also supports communication by WG officials of IMP outputs to senior ministerial staff or other stakeholders, such as the general public, unions, NGOs and environmental actors. This means that the modelling is appraised honestly and openly, and the results are interpreted in the context in which they were developed (Saltelli et al., 2020).

A further key element in securing trust in integrated models is compliance with government approved QA protocols; in the case of the IMP this was the UK Treasury's "Aqua Book" (HM Treasury, 2015). The Aqua Book QA ensures analyses are conducted in a transparent manner and puts an explicit focus on ensuring the findings are Repeatable, Independent, Grounded in reality, Objective, have Uncertainty managed and are Robust. This is demonstrated through the academic history of peer review of the component models, running independent QA (e.g. sensitivity testing) of the key model linkages, providing expert and end user assessments of the outputs, validating the results against observations where possible and being transparent about the uncertainties and limits of the QA that is possible (Voinov et al., 2016; Saltelli et al., 2020). However, traditional QA is not always possible due to a combination of: (i) the rapid evidence need, (ii) the lack of availability of suitable validation data, (iii) the complexity of the socio-environmental system that is being simulated, and (iv) the complexity of the linked modelling system (Robertson 2021). Nevertheless, these factors are not a barrier to Aqua Book compliance as it is possible to address uncertainty explicitly without formal uncertainty quantification. This was done using expert-informed statements on uncertainty, supported by frequent dialogue around accuracy and uncertainty between the IMP team and WG, which was considered sufficient for informing decisions around policy design (van Asselt and Rotmans 2002; Saltelli et al., 2020; Skea et al., 2021).

### 4.3. Rapid adaptability and application of integrated models

The policy environment has to react to political changes quickly and hence fast delivery of model outcomes for supporting policy design is crucial. However, many integrated models have long run-times and inflexible structures that limit their responsiveness (Anderson and Peters 2016; Gambhir et al., 2019). Several authors have called for greater flexibility in integrated modelling (Argent 2004; Ewert et al., 2009; Norling et al., 2021), including flexible integrated modelling architectures, and iterative evaluation and modification of scenarios informed by user feedback (IPBES, 2016; Jones et al., 2023).

The ability to rapidly adapt the IMP framework has been integral to its successful uptake across different policy departments across WG where policy questions can vary widely as well as shift over short time spans. This is supported by the soft-coupling approach to model integration, as 'people' (academics and WG working in partnership) are the enablers of fast model adjustment to evolving WG business-critical policy questions. This retains the active expertise in the model components within the IMP, facilitating the ability to address rapidly evolving policy needs in near real-time. The WG assessed this element of the IMP as "*essential*" in the survey stating that "*delivering at* pace *allows adaptation of policy thinking as outputs emerge*" and "*the rapidness of the IMP has meant the tool is more powerful*".

It is recognised that the choice of the soft-coupling approach to model integration may affect the degree to which temporal dynamics, feedbacks or formal uncertainty assessments are included in an integrated model due to the additional time needed to pass data between institutions with sufficient QA. This can be streamlined but will never be as fast as hard-coupled integrated models. Hence, decisions may need to be made on the relative importance of these issues to decision support *versus* the need for the integrated model to be rapidly customisable. The soft-coupling approach and modular nature of the IMP provides the flexibility to incorporate new or replace old component models within future platform developments as new policy needs emerge. There is, however, a tension between the downtime needed to add additional capability to the integrated model and the pace needed to deliver timely policy relevant work.

## 5. Final reflections and conclusions

The interactive and iterative process of co-creation and co-learning between WG and IMP modellers is consistent with the two main objectives of participatory modelling (Voinov and Bousquet, 2010): (i) developing shared knowledge and understanding of system behaviour, which has been realised through the co-development of model assumptions, heuristics and inputs in the IMP; and (ii) identifying and understanding the potential impacts of actions to support policymaking through the co-learning gained from presenting, critiquing and explaining the modelled system responses. This enabled members of WG to participate in all seven of the articulated core components for a participatory process identified by Voinov et al. (2016) from scoping through to evaluation of the outputs and outcomes, including facilitation of the transparency of the process. Even though the IMP has not been able to address all criticisms of integrated models (e.g. model structural uncertainty - Rounsevell et al., 2021; Brown et al., 2021a, 2021b), the continual bi-directional flow of information between modellers and stakeholders has facilitated a process of shared learning that has resulted in transparency, group validation and verification (Voinov and Bousquet, 2010), leading to trust in the modelling framework and its outputs in supporting decisions. Consequently, the IMP results have been used to inform decision-making and policy response across a range of rapidly evolving policy areas. We argue that the IMP is a rare example of the successful co-creation and application of an integrated model for decision support. This is reinforced by the quote below from the Welsh Government:

> *"The Welsh Government has made a significant investment in the development of the IMP. The modelling capability we now have is making a direct and ongoing impact upon how we operate, how we plan and how we will respond to the challenges we face. I'm confident that our investment will provide a significant return in helping every stage of our policy cycle, designing, delivering and evaluating better more impactful and cost effective polices."* **James Skates** (Head of Modelling, Geospatial and Monitoring; Welsh Government).

The transparency and trust in the IMP results have given momentum to cultural change within the WG where policy development is increasingly more evidence-based and iterative, with the policy and evidence teams having the space to challenge each other as the thinking evolves. As described by a key WG stakeholder, "*The IMP has brought extremely complex and often seemingly unrelatable evidence directly to the policy teams in a format which is accessible. This has enabled a step change to take place where high quality evidence is central to policy design*".

The lessons learnt from the development and application of the IMP offer transferable insights into the benefits, challenges and effort associated with the co-creation and co-learning needed to develop trusted and transparent integrated models that can support policy design. This partnership has demonstrated how the criticisms of many integrated models can be avoided through the ambition, bravery and vision to fund long-term modeller – stakeholder relationships; the openness of modellers and stakeholders to participate in bi-directional information and knowledge sharing; and the willingness of modellers to open their models, assumptions and inputs to scrutiny and challenge. Given the increasing recognition that many environmental, social and economic crises, such as climate change, biodiversity loss, food insecurity and global pandemics, are interconnected (Estoque 2023; IPBES 2020; IPBES-IPCC 2021; Schmidt-Traub et al., 2019), the demand for trusted and transparent integrated models is likely to escalate to support the development of holistic policies and actions that avoid unintended consequences, proactively tackle trade-offs and foster synergistic outcomes across sectors.

## Author contributions

P.A.H. and R.W.D. designed and led the research with contributions from all authors; P.A.H., R.W.D., K·B., J.C., I.D., A.F., R.G., M.H., I.P.H., M.H., L.J., T.M-M., D.S., G.S., F·S., S·S., A.T., B·W., F·W., S·N., P.T. and A.C.W. performed the research; K·B., J.C., I.D., A.F., R.G., M.H., I.P.H., M.H., D.S., F·S., S·S., A.T, B.W. and F.W. analyzed the data; K·B., J.C., I. D., A.F., R.G., M.H., M.H., L.J., D.S., F·S., S·S., A.T., B·W., F·W., E.C., R. W.M., S·N., V·S., J.S., P.T. and M.V. undertook model coding and programming support, and P.A.H., I.P.H., R.W.D., K·B., J.C., I.D., A.F., R.G., M.H., L.J., T.M-M., D.S., G.S., S·S., A.T. and F.W. wrote the paper.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: All authors report financial support was provided by UK Centre for Ecology & Hydrology. All authors report financial support was provided by the Welsh Government.

## Data availability

The data that has been used is confidential.

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## Appendix A. Supplementary data

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